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Assess Changes in Electric Vehicle Usage Behaviour: Comparison between 2018 and 2021

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Abstract-With advancements in power battery technology, all-electric driving range (AER) of electric vehicles (EVs) and charging infrastructures have improved significantly in recent years. These improvements may change usage behaviour and reduce range anxiety. Herein, this paper collects nearly 90,000 EV real-world operation data in 2018 and 2021. EV travel and plug-in habits are analysed with descriptive analytical methods and statistical tests. Range anxiety is also assessed using the ordinary least squares algorithm. The results show a 15% rise in daily distances for electric taxis, alongside a 26.5% increase in AER and a 29.9% increase in charging power. In contrast, personal EV travel distance shows little change, despite a 50.8% increase in AER and a 13.9% increase in charging power. The results also indicate that as charging power increases, there is a significant decline in range anxiety calculated by the state-of-charge before charging, a trend not observed with increasing AER.

Keywords- Electric vehicle; real-world data; vehicle kilometre travelled; comparative study

1. Introduction

Electric vehicles (EVs) are increasingly replacing internal combustion engine vehicles (ICEVs) as part of the global effort to reduce carbon emissions and air pollutants associated with traffic (Isik et al., 2021; Wei et al., 2021). ICEVs constitute threatening adverse environmental impacts, which may continue to persist over an extended period (Xia et al., 2023). There is a notable trend towards the electrification of light-duty passenger cars in China, Japan, the USA, and Europe, which collectively represent over 50% of the global market. Moreover, with the increasing daily travel demand, the all-electric driving range (AER) of EVs has also grew gradually in these years and the deployments of EV charging facilities also increase significantly. However, the growing adoption of EVs with higher battery capacities and less charging duration raises a question: How will users' vehicle usage habits change based on different AERs and charging powers? (Langbroek et al., 2018; Falchetta and Noussan, 2021; Calearo et al., 2021; Zhao et al., 2023a; Williams et al., 2024)?

The usage behaviour features of EVs are critical for both automobile manufacturers and power suppliers, that can provide a comprehensive understanding about the usage demand and energy consumption, especially in the scenario with a high EV penetration in 2030 and even further. For example, designing EVs with large battery capacities could lead to material waste and increased energy consumption, ultimately placing additional strain on the electrical grid (Giansoldati et al., 2018; Liu et al., 2023). Langbroek et al. (2018) suggested that it will be useful to analyse the usage changes of EVs from the early stage, because the EV has been a relatively new mobility carrier in the last decade. In the early stage of EV deployment, drivers facing range limitations are more likely to make use if alternative means of transportation. Inadequate planning of EV charging infrastructure can also result in inconvenience for users. Moreover, some private users would like to make an EV as secondary rather than primary household cars in cities with license plate restrictions (Zhao et al., 2023a). However, much progress has been developed of EV power battery technologies and a number of EV charging infrastructures in the past five years (Zhao et al., 2023b).

Data-driven investigations (Zhao et al., 2021; Gellrich et al., 2022; Hu et al., 2022; Lei et al., 2022; Yang et al., 2022; Siddique et al., 2022; Cui et al., 2022, 2023; Tian et al., 2023; Wang et al., 2023; Zhao et al., 2023c; Zhang et al., 2023; Hecht, 2023) are the primary approaches to solve this problem, providing detailed and comprehensive information. This method offers the most direct insight into vehicle usage patterns. Calearo, Marinelli and Ziras (2021) conducted a comprehensive review of major studies on EV usage, including surveys, trials of ICEVs and EVs, and charger trials prior to 2022. This literature review was both thorough and insightful, offering a solid framework for further research. It should be noted that some available data is considerably older than ten years, and new data from today may be already different from users driving in 2025/2030. Therefore, new data should be analysed to provide a state-of-the-art understanding. Built on the review of data sources for EV charging and driving studies provided in previous study (Calearo et al., 2021), this paper focuses on some data-driven studies published after 2022. In general, the data can be collected from the vehicle side or charging station side. We summary the purpose for analysing EV operation data into behaviour analysis, load analysis, charging demand, energy consumption and range anxiety. A summary of the relevant literature is provided in **Table 1**.

The volume of data collected for EV usage behaviour analysis has shown a noticeable increase compared to earlier studies (Cui et al., 2022; Hu et al., 2022; Sandström et al., 2023; Siddique et al., 2022; Zhang et al., 2023; Zhao et al., 2023c). Additionally, the application scenarios analysed become more abundant (Cui et al., 2022, 2023; Pan et al., 2023). However, these studies mostly focused on the behaviour description rather than the changes with different vehicle technologies and charging facility deployments. For example, Zhao et al., (2021) utilised a large-scale EV operation data to assess the battery utilisation of different application scenarios. The study reported that light-duty EVs with higher battery capacity will always suffer higher maximum unavailable battery state-of-charge (SOC). They also provided an integrated data-driven model for large-scale EV operation analysis. The impact of the EV charging on the electricity grid has been concerned more due to the higher electricity demand (Chen et al., 2018; Muratori, 2018; Powell et al., 2022). These studies simulated the EV usage based on the limited features collected from real-world data or questionnaires.

Considering the long-term usage behaviour analysis, Hecht (2023) collected a long-term EV charging record from the charging station from 2019 to 2022, and noticed that the mobility pattern changed over time has an impact on the EV charging prediction model performance. Lyu et al. (2024) collected the EV operation data in some metropolis of China from 2019 to 2020, and assessed the carbon reduction and emission reduction. Jenn (2020) analysed the emissions benefits of EVs in Uber and Lyft ride-hailing services. The charging records between January 2017 to May 2018 have been collected to calculate the average charging emissions. Nevertheless, the AER was often ignored owing to the coverage of samples taken. This requires not only that the data collected has an enough time span, but also that the vehicle battery technology in the area where it is collected is rapidly evolving. Using the data from charging station side can support the operation of the power distribution network, but it is not possible to create a complete cycle of energy use and consumption. Thus, the paper aims to provide a comprehensive data analysis for the EV usage behaviour changed with different AER distributions and charging power levels to fill this gap.

A large-scale, long-term and unique EV operation data collected from the National Big Data Alliance of New Energy Vehicles OpenLab in China provided us a substantial environment to address this study. The main contributions of this paper are provided as follows:

(1) The paper establishes a real-world EV operation database including 1,352 electric taxis and 7,639 personal EVs operating in 2018, and 1,140 electric taxis and 85,518 personal EVs in 2021 in Beijing. The data samples are more than that of most previous studies.
(2) Based on these real-world data, the paper analyses the improvements of AER and charging power, and then calculates distance-based, utilisation-based, SOC-based and time-based indicators to assess the potential changes in travel habits and plug-in habits with descriptive methods (average and quartiles) and statistical tests. The quantitative results are provided in detail, which was always examined by questionnaires.
(3) The paper finally examines the changes of range anxiety, which is concerned by most potential and current EV users, based on the remaining mileage and SOC before charging. An ordinary least squares (OLS) algorithm is used to assess the impact of AER and charging power improvements on the range anxiety. The assessment has not been addressed using this sort of large-scale real-world dataset. The results indicate that as charging power increases, there is a significant decline in range anxiety.

Table.1 Literature review of the new data resource after 2022.

Refs.	**Data resources**	**Purpose**
Cui et al., (2022)	26,060 personal EVs, electric taxis and rental EVs operating in Beijing in 2018	Behaviour analysis
Yang et al., (2022)	76,774 personal EVs operating in Beijing in 2018	Behaviour analysis
Siddique et al., (2022)	189,864 supply-side charging session data over 13 months from 821 charging stations in Illinois from ChargePoint	Behaviour analysis
Gellrich et al., (2022)	Data from 3,279 charging stations with 6,615 EV service equipment in three weeks	Behaviour analysis
Tian et al., (2023)	168 personal EVs operating in Beijing in 2020	Behaviour analysis
Hu et al., (2022)	228,440 charging records of 7,426 light-duty EVs in 2019.	Behaviour analysis
Zhao et al., (2023c)	230,000 light-duty EVs operating in Beijing in 2021	Behaviour analysis Load analysis
Zhang et al., (2023)	25,489 private EVs and electric taxis operating in Beijing	Charging demand
Cui et al., (2023)	1,458 private EVs, electric taxis and rental EVs operating in Beijing in 2018	Charging demand
Wang et al., (2023)	2,529 battery swapping events from 36 battery swap stations in Beijing in 2019	Charging demand
Lei et al., (2022)	20,130 electric taxis operating in Shenzhen in 2019	Charging demand
Hecht, (2023)	Charging records collected from charging stations in Germany from 2019 to 2022	Charging demand
Pan et al., (2023)	7 electric taxis, electric online car-hailing, and personal EVs in Shanghai in 2019	Energy consumption
Yang et al., (2023)	2,658 personal EVs operating in Beijing in 2018	Load analysis
Sandström et al., (2023)	159,000 charging sessions from 900 chargers from Swedish EV charging product supplier	Load analysis

This paper is organized as follows: **Section 2** introduces the data collection and processing methods. **Section 3** provides an analysis of AER from vehicle side and charging power from charging facility side. **Section 4** provides an understanding analysis of the vehicle kilometre travelled (VKT), battery utilisation rate and distance between two continues charges for EVs. **Section 5** analyses the EV plug-in charging habits changes, including plug-in time and battery SOC relations, power selection and remaining mileage when charging. Range anxiety is assessed based on EV travel habits and plug-in charging habits in **Section 6**, followed by a discussion about behaviour changes and range anxiety changes. The last section presents the conclusions and limitations based on the results of this work.

2. Data collection and illustration

The EV operation data are collected from the National Big Data Alliance of New Energy Vehicles OpenLab in this study. The data collection standard is GB/T 32960-2016 (https://www.chinesestandard.net/PDF.aspx/GBT32960.2-2016). The EV operation data in March 2018 is used as a comparison group for the benchmark. To eliminate the impact of COVID-19 on user behaviour, the situation in March 2021 is used to compare and analyse the behaviour changes, because there was almost no lockdown in this period in Beijing. Finally, considering the public usage of the light-duty passenger cars, there are 1,352 electric taxis operating in 2018 and 1,140 in 2021, respectively. The sample represents about 15% of the total electric taxies in Beijing in 2021. This study also assesses the behaviour changes for the personal EV usage. There are further 7,639 personal EVs collected during 2018, while the sample amount has increased into 85,518 in 2021. The sample represents about 25% of the total personal EVs in Beijing in 2021.

As shown in **Table 2**, vehicle operation data, battery operation data and timestamp can be collected from the data platform. According to the vehicle model, the paper collects AER and battery capacity from the disclosure by the institutes of the government. There is a raw operating data example of an EV provided in **Appendix A**. The vehicle state includes driving, parking and grid charging. Based on the integration of the vehicle state, the raw EV data are processed into a statistical database. There is also a statistical data example provided in **Table 3**. The initial and end states of the vehicle and battery are extracted from the raw data (e.g., start timestamp, end battery SOC).

Table 2 Data illustration.

Resource	Item	Unit
From the platform	Vehicle model	-
	Vehicle ID	-
	Velocity	km/h
	Mileage	km
	Battery SOC	%
	Battery pack voltage	V
	Battery pack current	A
	Vehicle state	Driving/Charging/Parking
	Timestamp	hour:minute:second
From the disclosure	AER	km
	Battery capacity	kWh

Table 3 Statistical data example of an EV.

Vehicle state	Start timestamp	End timestamp	Start battery SOC	End battery SOC	Start mileage	End mileage
Charging	2018/3/1 0:27	2018/3/1 4:35	52.0%	100.0%	88,967.0 km	88,967.0 km
Parking	2018/3/1 4:35	2018/3/1 8:05	100.0%	100.0%	88,967.0 km	88,967.0 km
Driving	2018/3/1 8:05	2018/3/1 12:36	100.0%	40.0%	88,967.0 km	89,056.0 km
Parking	2018/3/1 12:36	2018/3/1 13:20	40.0%	40.0%	89,056.0 km	89,056.0 km
…	…	…	…	…	…	…

3. Vehicle- and Charging Technology Improvement

This section focuses on two types of technology improvements, including enhancing AER from the vehicle side and improving charging power from the facility side (Noel et al., 2020). These two factors are likely the most critical indicators of changes in user behaviour, which have been widely discussed in previous studies (Langbroek et al., 2018; Lin and Yang, 2024; Williams et al., 2024; Zhang et al., 2021). Rather than delving into the technical theory behind these advancements (such as higher density battery materials), the practical situations are focused on in this section.

3.1 AER Changes

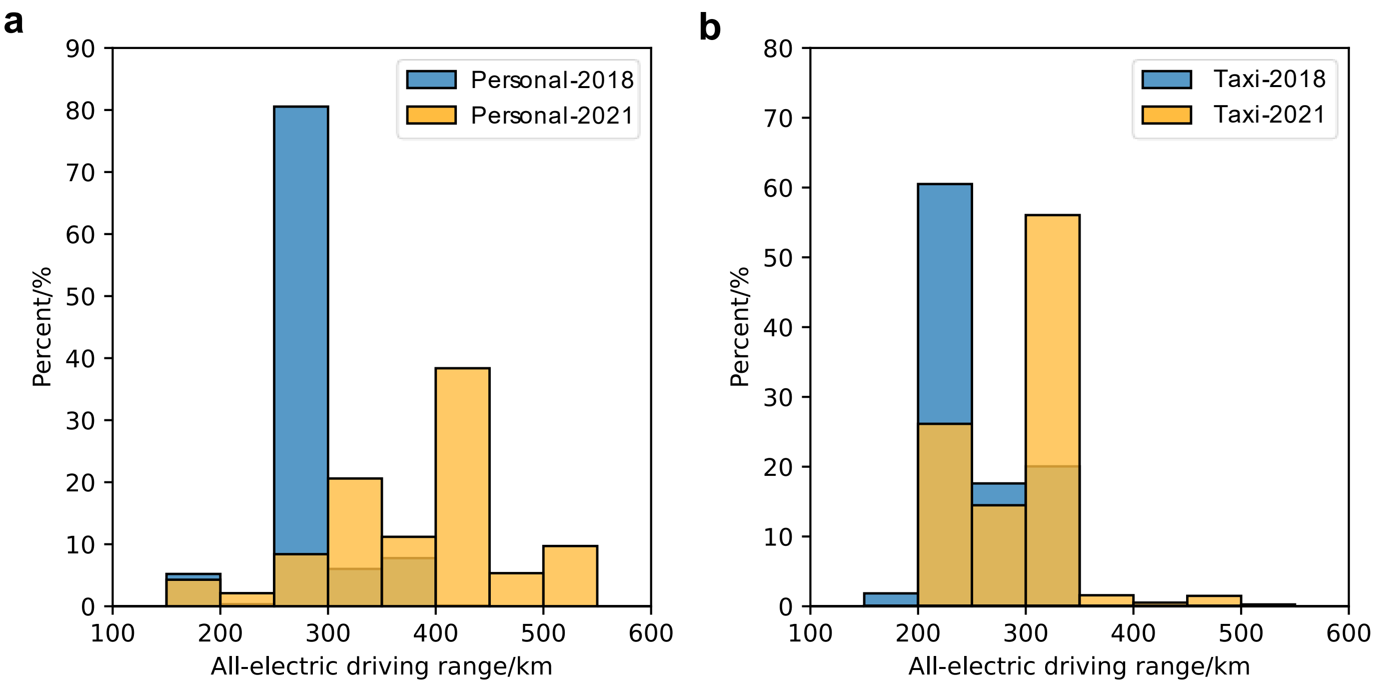

Fig.1. AER distributions of **a** personal EVs and **b** electric taxis in 2018 and 2021.

AER is very critical to EV users, directly affecting their driving experience and purchase decision (Franke and Krems, 2013; Giansoldati et al., 2018; Zhou et al., 2023). The AER distributions of personal EVs and electric taxis are provided in **Figs. 1 a-b**, respectively. More than 70% of personal EVs have an AER between 250 and 300 km in 2018. While the AER selected by subsequent users is much higher in 2021. Significantly, the proportion of EVs with AER between 400 and 450 km is more than 30.0%. The major groups of electric taxis have transited from the interval between 200 and 250 km to that of more than 300 km between 2018 and 2021.

A Kolmogorov-Smirnov normality test is first conducted to assess the shape of the distribution (Habla et al., 2021; Huang et al., 2023). The normality results of each AER distribution indicate a significant violation of the normality assumption ($p < 0.05$). Due to the non-normality of data, the Mann-Whitney U (M-W U) test is performed to determine whether there is a statistically significant difference between two years (Huang et al., 2023). Although the comparison only has a 3-year difference, the advanced power battery technology has improved the maximum AER significantly for personal EVs (an average increase of 50.8%, M-W U test, $p<0.001$) and slightly for electric taxis (an average increase of 26.5%, M-W U test, $p<0.001$) in the case of passenger car electrification in Beijing.

3.2 Charging Power Changes

Battery charging technology is another important factor in determining EV usage behaviour. In terms of charging technology standards, there are many different requirements and ranges in different regions. Amer et al. (2024) summarised recent charging technology standards which can be inferred that it is hard to distinguish the charging type only with charging current, voltage and power. There is also a significant data fluctuation in the real-world data collection. Moreover, due to the charging records being collected from the vehicle side, therefore, it could be difficult to recognise the direct current (DC) charging or alternating current (AC) charging directly. However, focusing on the EV charging load impact on the power distribution network, fast-charging or slow-charging loads are also important for the power distribution operation. Therefore, considering the standards in China, Europe and the USA, 10 kW is used as a threshold to distinguish slow-charging (including AC 1.9 kW, 3.8 kW, 4 kW, 7 kW, 7.6 kW and 8 kW) and fast-charging (including AC 15.3kW and 27.7 kW and DC). The charging power calculation method is provided in **Appendix. B**.

The slow-charging power distributions are shown in **Figs. 2a-b**. Charging power is categorised into three clusters: 1.9 kW, 4 kW, and 7 kW based on the distributions. However, no strict clustering algorithm is applied due to fluctuations in real-world data. By 2021, more chargers in the cluster of 7 kW are deployed for personal EVs and electric taxis, accounting for 23.1% and 42.3% of the total, respectively. Some private chargers constructed in 2018 with 4 kW are still survived 2021. Only a small number of personal EV owners install 1.9 kW chargers, as these require private space, which is not feasible for most taxi drivers. As a result, taxi drivers rely more on public chargers. Additionally, the increase in fast-charging power is notable, with more chargers exceeding 45 kW being used in 2021 for both personal EVs and electric taxis (see **Figs. 2c-d**). Statistically, the average fast-charging power increased by approximately 13.9% for personal EVs (M-W U test, $p<0.001$) and 29.9% for electric taxis (M-W U test, $p<0.001$).

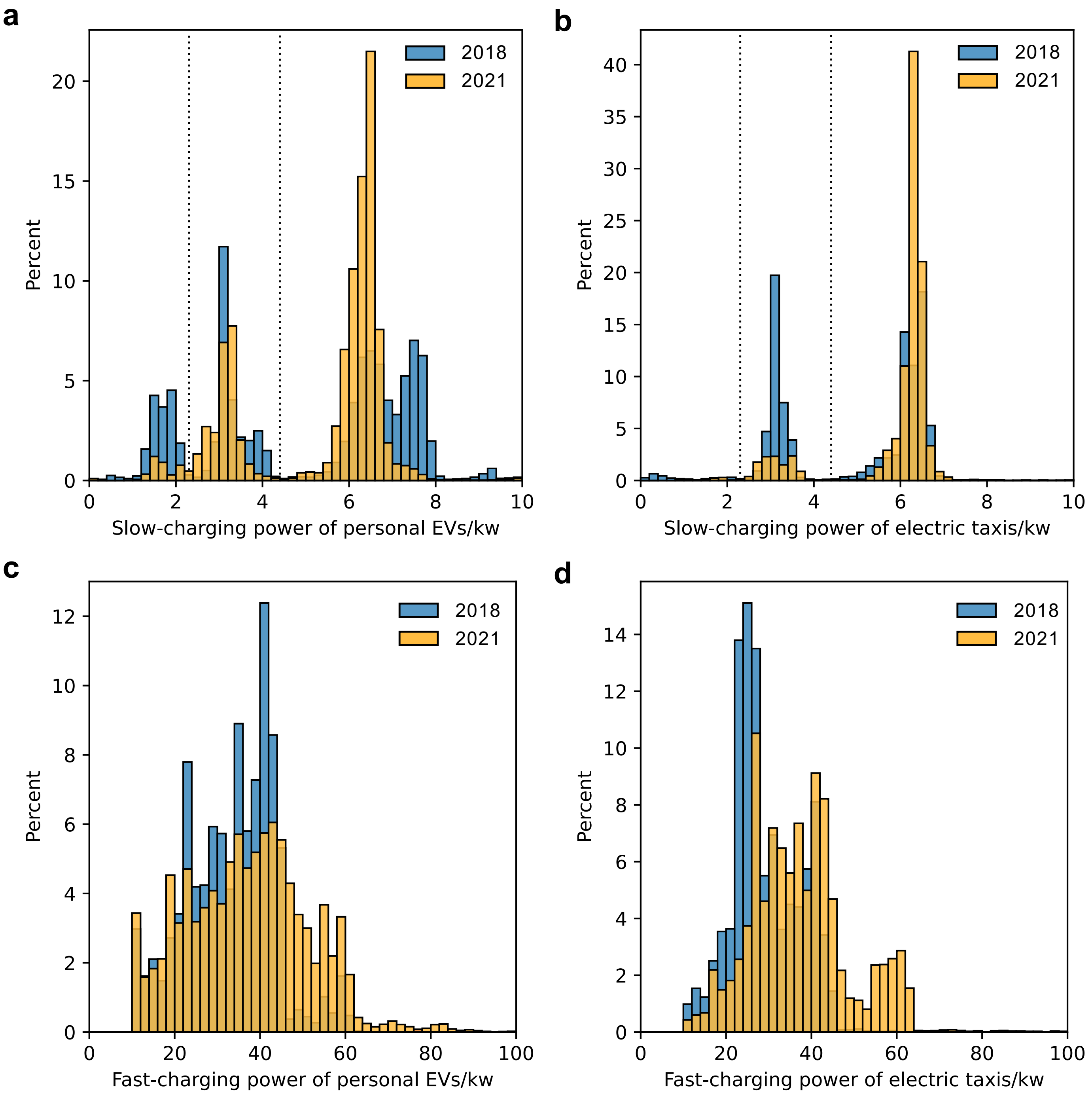

Fig.2. Slow-charging power distributions of **a** personal EVs **b** electric taxis and fast-charging power of **c** personal EVs **d** electric taxis in 2018 and 2021, respectively.

4. Understanding EV Travel Habits.

Owing to the obviously different travel demand on weekdays and weekends, the travel habit features of EVs have been divided into these two periods. The study focuses on the user-based analysis rather than result of a certain day or period. Therefore, one EV user can only get one feature in the statistical period. For example, considering the daily travel distance of one EV in a month, it is more suitable to use the average result rather than about 30 results to describe the user's habits.

4.1 Average Daily VKT

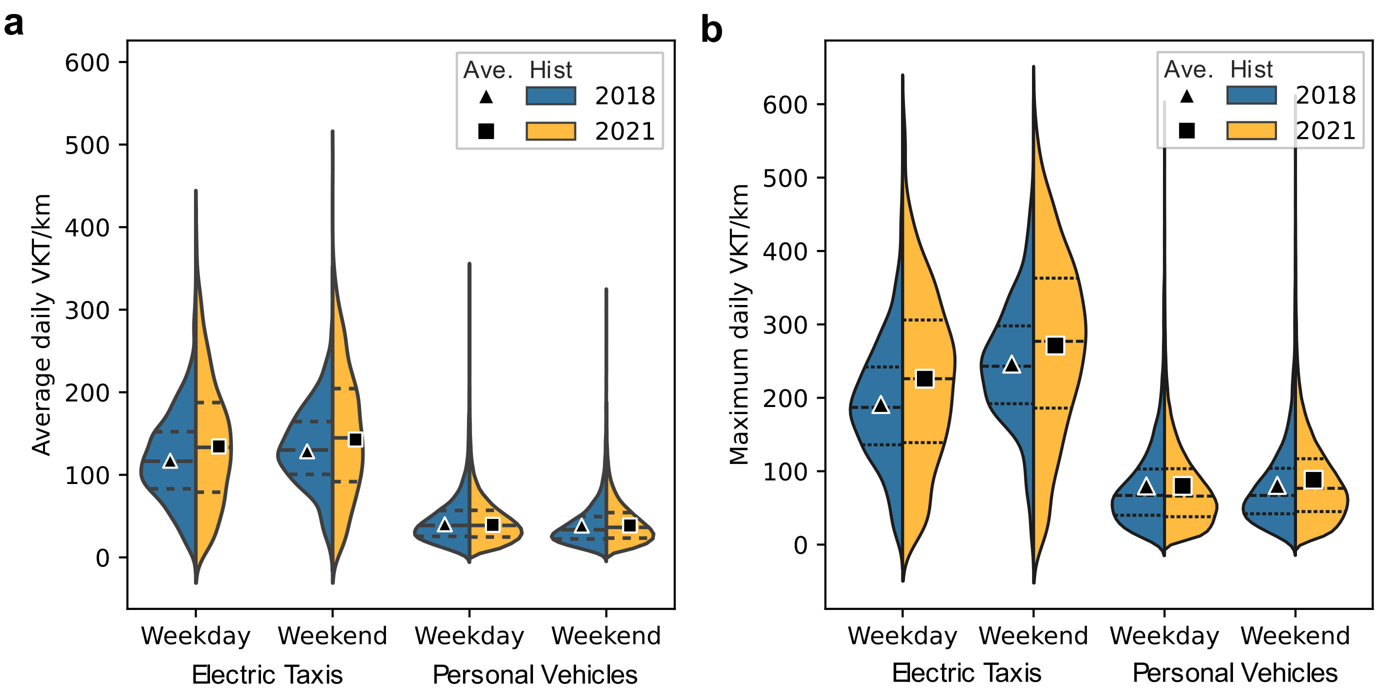

Fig.3. Daily VKT of EVs on weekdays and weekends operating in 2018 and 2021. a Average daily VKT distributions for electric taxis and personal EVs. **b** Maximum daily VKT distributions for electric taxis and personal EVs.

This paper examines the daily VKT of EVs through descriptive analysis and statistical tests. The comparisons are based on the day of use and the year of use. The method for calculating VKT is detailed in **Appendix C**, with results presented in **Fig. 3a**. The specific statistical results are provided in **Appendix E**. The analysis compares differences between two years within the same application scenarios and time periods. For the average of electric taxis operating on weekdays, the difference between 2018 and 2021 is statistically significant at the 1% level (M-W U test, $p<0.001$). The results also show an increase of about 3 km in the average daily VKT of personal EVs on weekdays between 2018 and 2021, with the difference in means being statistically significant (M-W U test, $p<0.001$). On weekends, there is a statistically significant increase in the average daily VKT for electric taxis (M-W U test, $p<0.001$), no significant change is observed for personal EVs during the same period (M-W U test, $p=0.067$). In summary, comparing the results between 2018 and 2021, the average daily VKT of personal EVs increased by 7.9% ($p<0.001$) on weekdays, with no significant change observed on weekends. In contrast, the average daily VKT of electric taxis increased by 13.5% ($p<0.001$) on weekdays and 17.1% ($p<0.001$) on weekends.

In terms of the distribution shape, the quartiles of personal EVs operating on weekdays show a slight increase, particularly in the third quartile, which rises from 49.4 km to 54.2 km. The first quartile of electric taxis slightly decreases on weekends, indicating a reduction in low-mileage electric taxis, while the third quartile increases significantly from 152.2 km to 187.5 km, reflecting a notable rise in higher daily VKT. On weekdays, the third quartile shows a substantial increase from 164.4 km to 204.4 km, also suggesting more electric taxis with longer trips.

The maximum daily VKT is calculated to assess the maximum usage intensity for EV users (see **Fig. 3b**). It can be noted that the average maximum daily VKT of personal EVs change from 80.7 km to 88.3 km on weekdays (M-W U test, $p<0.001$) and from 80.0 km to 77.8 km on weekends (M-W U test, $p=0.003$); while electric taxis increase slightly from 246.0 km to 271.8 km on weekdays (M-W U test, $p<0.001$) and from 190.9

km to 225.6 km on weekends (M-W U test, $p<0.001$). All above, under the condition of $p<0.001$, the maximum daily VKT of personal EVs has increased by 9.4% on weekdays, while the results of electric taxis increase 10.4% on weekdays and 18.3% on weekends, respectively.

4.2 Average Battery Utilisation Rate

Considering the potential material waste of the increasing AER, battery utilisation rate is calculated to assess the proportional values rather than absolute values. Because larger battery capacity sometimes may result in more purchase cost (Yang, 2022), higher energy consumption (Nykvist et al., 2019; Yang, 2022; Zhao et al., 2023) and even more environmental pollution when recycling batteries (Dehghani-Sanij et al., 2019). It should be found that the maximum battery utilisation rate for personal EVs in 2021 is lower than that in 2018 (see the comparisons of green- and blue line, and orange- and red line in **Figs. 3a-b**). The calculation method is provided in **Appendix D**. Specifically, about 2.1% of personal EV users had a maximum daily VKT exceeding 100% AER in 2018, but this situation almost disappears by 2021. Almost no personal user travels more than the vehicle AER in one day. No more than 24.5% (9.3%) of personal EV users uses more than 50% of AER in a day on weekdays (weekends) in 2018. This proportion becomes 15.7% on weekdays and 9.5% on weekends in 2021. The increasing AER would keep more battery materials in standby states in the daily usages of personal EVs. The travel demand determines the battery usage. In terms of application scenarios for electric taxis, the maximum battery utilisation rate to reach 100% AER drops from 59.1% to 48.2% on weekdays between 2018 and 2021, while it has a similar proportion on weekends (35.3% and 33.4%, respectively). It can be illustrated that although daily VKT of electric taxis has increased significantly, the battery material usage intensity still declines slightly with the increasing power battery capacity.

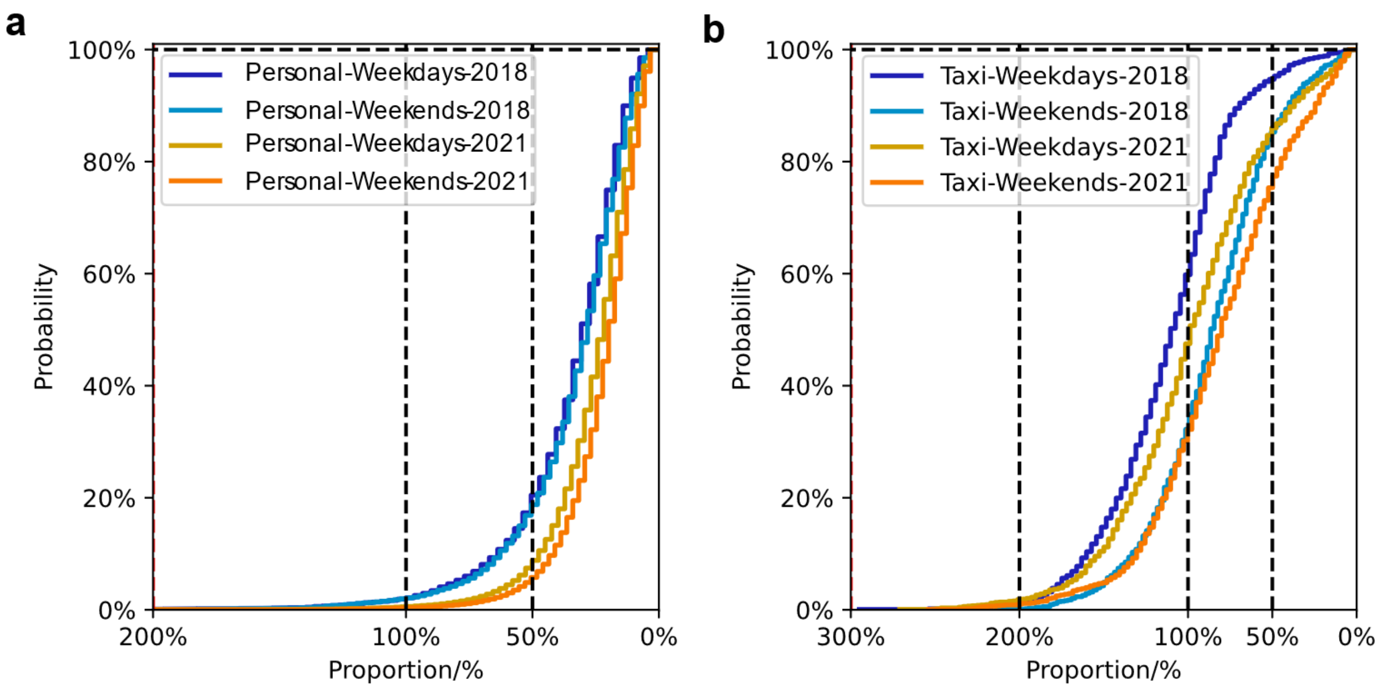

Fig.4. Battery utilisation rate for EVs operating in 2018 and 2021. The cumulative density function of the maximum battery utilisation rate for **a** personal EVs and **b** electric taxis, respectively.

4.3 Distance between Two Charges

Another distance-related analysed in this paper is the distance travelled between two continuous charging events. Similarly, the descriptive results are provided firstly and examined with M-W U test to illustrate the significance difference, shown in **Fig.5.** The specific figures are provided in **Appendix E**.

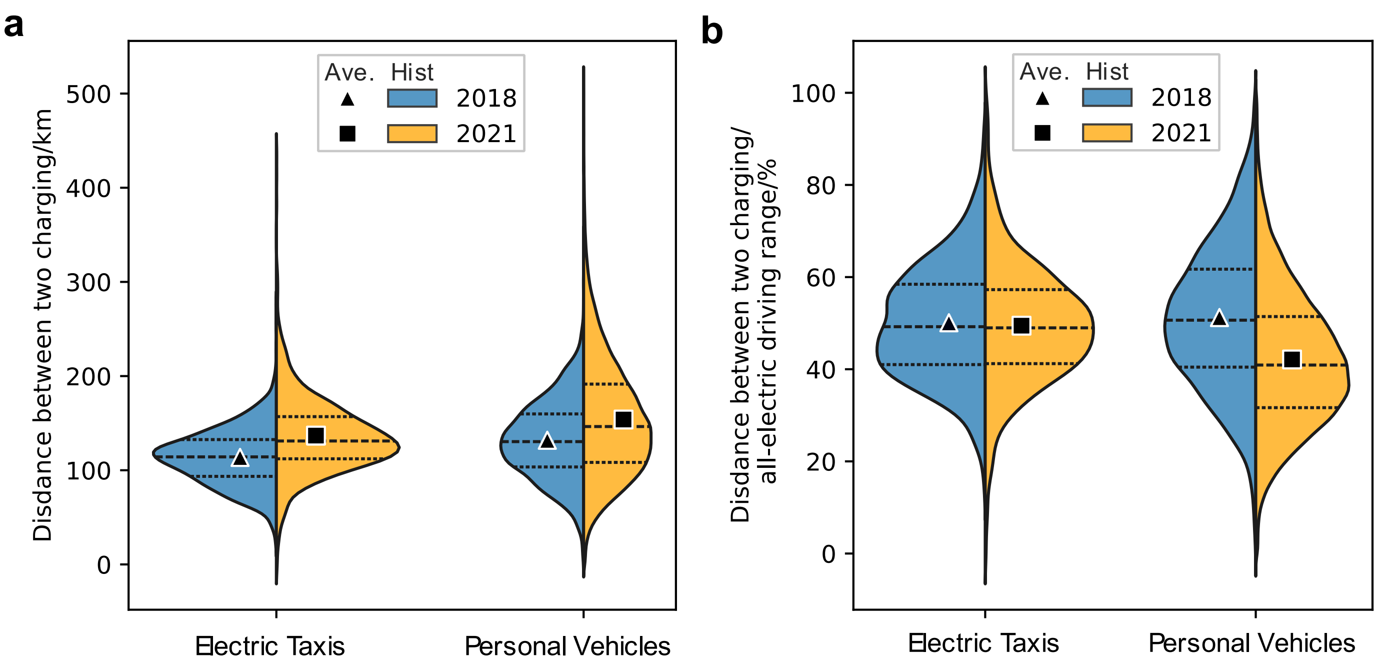

Fig.5. **a** Distance and **b** battery utilisation rate between two continuous charging events.

On the one hand, the average of electric taxis increases by approximately 20.0% from 113.7 km to 136.5 km (M-W U test, p<0.001), while the average distance of personal EVs increase by 16.7% from 131.9 km to 153.9 km (M-W U test, p<0.001). In terms of quartiles, the first quartile of personal EVs increases slightly (approx. 4.6%) while the third quartile increases significantly (approx. 19.8%), illustrating significant growth in personal users with higher distance travelled between two charges. Distance between two charges of electric taxis in the first quartile increases from 93.5 km in 2018 to 112.3 km in 2021, the third quartile increases from 132.6 km to 156.9 km, and the median increases from 114.2 km to 131.1 km. It suggests that the distributions of electric taxis move in the direction of longer mileage.

On the other hand, with the increase of the AER, it can be noted that the battery utilisation rates (i.e., the proportion between distance between two continuous charging events and AER) have a similar distribution for electric taxis in 2018 and 2021. The average rate only changes from 50.1% to 49.5% (M-W U test, p=0.231). There are also no major differences in the distribution of quartiles with an average AER increase of 26.5%. In contrast, the total distribution of personal EVs decreases significantly. The average rate reduces from 51.2% to 42.1% (M-W U test, p<0.001).

5. Understanding EV Plug-In Charging Habits.

EV charging plug-in habits should be focused on much more, especially for the ramping EV amount in recent years. Understanding when, where, and how often drivers plug in their EVs is crucial for optimising charging infrastructure and energy management (Li et al., 2023; Powell et al., 2022). As the EV market expands, focusing on charging behaviours can help prevent grid overload (Williams et al., 2024), keep the safety of power quality (Kalla et al., 2019), improve charging station availability (Bin Irshad et al., 2020), and enhance overall user experience. Specifically, plug-in time and plug-in battery SOC determine the influence period of EVs on the power gird. Power selection affects the magnitude of impact. Plug-in battery SOC and remaining mileage represents the attitude of EV users. The analysis and comparison not only focus on individual features but also related these features with different application scenarios and different charging levels in different years in this section. Different from the travel habits, we provide the plug-in charging behaviour feature distributions from event-based and analysed the total probability changes from user-based.

5.1 Plug-in Time and Battery SOC

The first finding of plug-in charging habits is about the relationship between EV charging plug-in time and plug-in battery SOC. Because the operation of the power distribution network has a strong periodicity, the plug-in time and access duration both have an implication on the peak-to-peak load and peak-filling capacity. The results for electric taxis are provided in **Fig.6**. The time distributions have shown significant changes for both fast- and slow-charging on weekdays and weekends between 2018 and 2021 (all M-W U test, $p<0.001$). Previous fast-charging habits from 9 a.m. to 6 p.m. transfers into a significant peak at 16:00 p.m. Some other fast-charging events can be found after 11 p.m. until the morning-peak. While previous slow-charging habits concentrate at around 10 p.m. transfers into other time slots, therefore, we compare and analyse the time transition between two continuous charging events. It's important to note that in 2018, most taxi drivers charge their vehicles at around 10 p.m. The percentage of slow charging at 10 p.m. on two continuous days is about 5.7%. The proportion of transitions between charging from 10 a.m. to 2 p.m. and from 6 p.m. to 10 p.m. reaches 26.5%. However, by 2021, fast charging becomes more prevalent, leading to a significant drop in slow charging at night, with the percentage of charging at 10 p.m. falling to less than 1% on both the day before and the day after. In contrast, the proportion of transitions between two charges from 11 a.m. to 3 p.m. and from 8 p.m. to midnight rises to 25.1%.

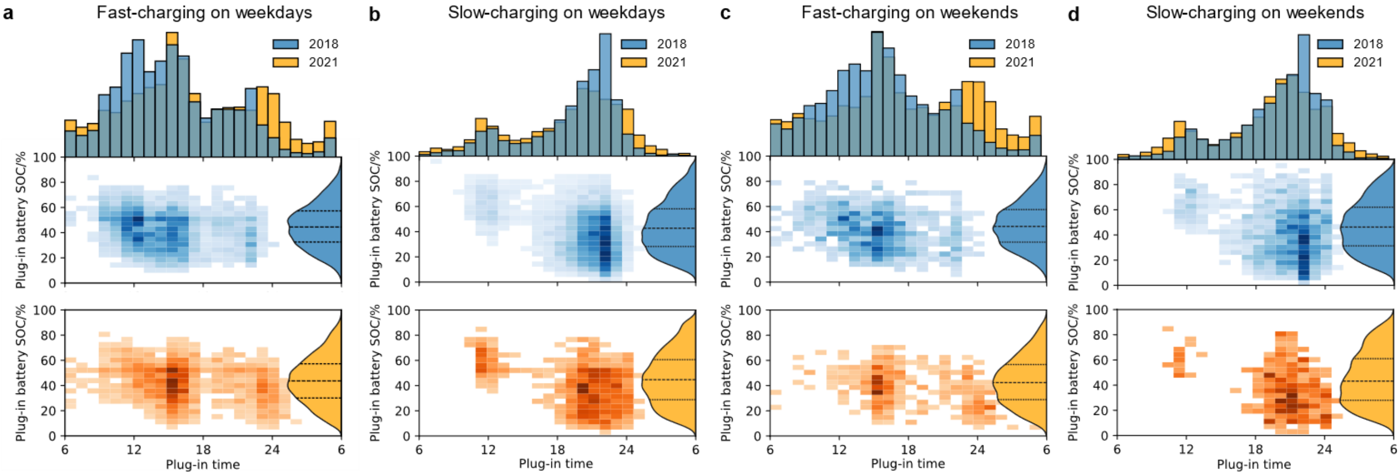

Fig. 6 Electric taxi plug-in time and initial battery charging SOC. a Fast-charging habits and **b** slow-charging habits on weekdays; **c** Fast-charging habits and **d** slow-charging habits on weekends.

In terms of the plug-in battery SOC of electric taxis, the average values and quartiles are provided in **Table 4**. There shows a negligible change in average slow-charging initial battery SOC on weekends (M-W U test, $p=0.618$), while a significant change of fast charging (M-W U test, $p<0.001$). However, from the perspective of quartiles, there shows a trend moving to lower SOC. Moreover, the average of fast-charging initial battery SOC on weekdays is almost no change (M-W U test, $p=0.271$), while the average of slow-charging increases approximately 2.5 % (M-W U test, $p<0.001$). There is also a similar trend in quartiles.

Table 4 Statistical results of the initial battery SOC for electric taxis in 2018 and 2021

Day	Mode	Year	Average/%	First quartile/%	Median/%	Third quartile/%
Weekend	Fast	2018	43.4	28.0	42.0	57.0
		2021	41.4	25.0	40.0	56.0
	Slow	2018	44.9	27.0	44.0	62.0
		2021	44.6	24.0	42.0	63.0
Weekday	Fast	2018	43.8	30.0	43.0	57.0
		2021	43.5	28.0	43.0	58.0
	Slow	2018	42.5	25.0	41.0	58.0
		2021	45.1	26.0	44.0	62.0

The results of personal EVs are provided in **Fig.7.** The fast-charging habits have not changed too much on weekends between 2018 and 2021 (M-W U test, $p=0.025$), whereas there has been more fast-charging at morning- and evening peaks on weekdays in 2021 than that in 2018 (M-W U test, $p<0.001$). More concentrated distribution of the slow-charging plug-in time around 6 p.m. to 8 p.m. is observed both on weekdays (M-W U test, $p<0.001$) and weekends (M-W U test, $p<0.001$) in 2021 than that in 2018. However, this period is the evening peak of the power grid. The proportion of the charging events between 8 p.m. and 2 a.m. reduces from approximately 28.1% (~30.2%) to 21.4% (~22.8%) on weekends (weekdays), while the proportion of the period between 6 p.m. to 8 p.m. increases about 4.3% (~9.2%) in 2021. The shift on weekdays is more significantly. Although the slow-charging power remains concentrated at the original levels (see **Fig. 2**), it can be inferred that more EV charging impact for personal EVs may be on the night peak of the power distribution network, especially with a ramping deployment amount.

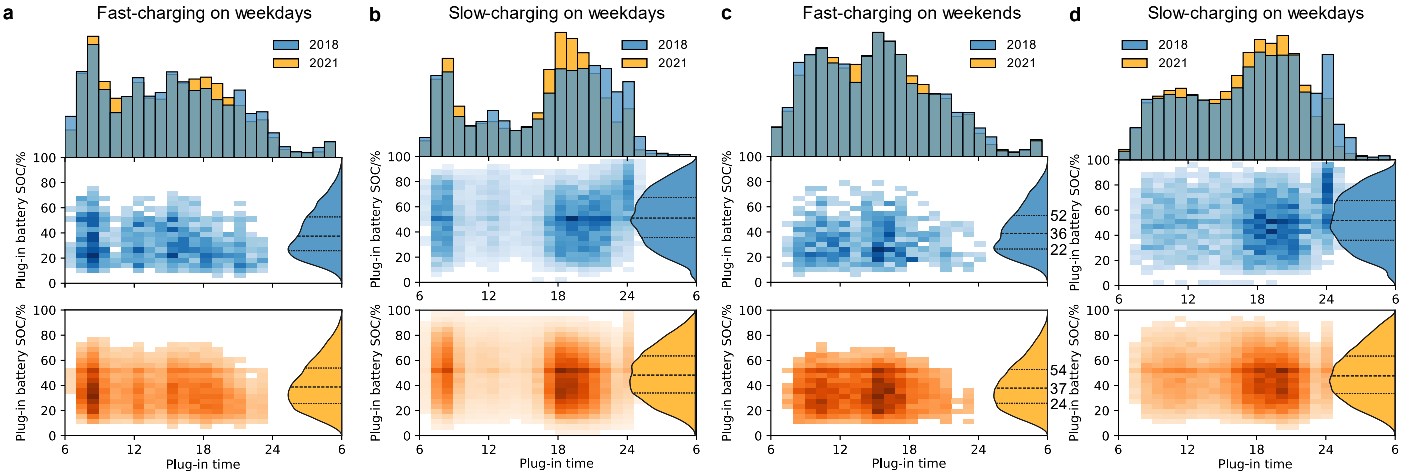

Fig. 7 Personal EV plug-in time and initial battery charging SOC. a Fast-charging habits and **b** slow-charging habits on weekdays; **c** Fast-charging habits and **d** slow-charging habits on weekends.

In terms of plug-in battery charging SOC of personal EVs, shown in **Table 5,** the average changes significantly both for fast- (increase about 2.0%) and slow-charging (reduces about 2.0%) on weekdays, and slow-charging on weekends also has a significant change (also reduces about 2.8%). However, the change of average fast-charging plug-in battery SOC doesn't change a lot (M-W U test, p=0.025). Furthermore, the quartiles of fast charging all increase slightly, while the values of slow charging reduce a few with more pronounced in high SOC intervals. Nevertheless, all plug-in battery SOC doesn't change a lot, and it is only a relative value involving battery capacity. Thus, it is necessary to assess the absolute value of the changes considering AER increases.

Table 5 Statistical results of the initial battery SOC for personal EVs in 2018 and 2021

Day	Mode	Year	Average/%	First quartile/%	Median/%	Third quartile/%
Weekend	Fast	2018	38.4	22.0	36.0	52.0
		2021	39.1	24.0	37.0	53.0
	Slow	2018	50.8	33.0	51.0	69.0
		2021	48.0	32.0	47.0	64.0
Weekday	Fast	2018	37.9	22.0	35.0	52.0
		2021	39.9	24.0	38.0	54.0
	Slow	2018	50.5	33.0	50.0	68.0
		2021	48.5	33.0	48.0	64.0

5.2 Charging Power Selection

The charging power selection distributions in each hour of the day are shown in **Fig.8**. It can be noted that the charging method of personal EVs between weekdays and weekends are similar in each year. However, more slow-charging proportion is observed in 2021 than in 2018 during most hours in a day. Conversely, electric taxi drivers have more intentions to charge the vehicle with a fast-charging method. The main difference between 2018 and 2021 is the proportion of the fast charging for electric taxis during the period of the night peak and the early morning. In addition, the percentage choosing fast charging between 10 a.m. and 12 a.m. on weekdays and 8 a.m. and 12 a.m. on weekends drops by 8.2% and 14.1% on average, respectively. In general, the proportion of fast charging for personal EVs is about 22.2% in 2018 and 23.9% similarly in 2021, while the fast-charging proportion for electric taxis is about 43.3% in 2018 and increased into 56.1% in 2021. Significant fast-charging technology applications of electric taxis was observed in 2021.

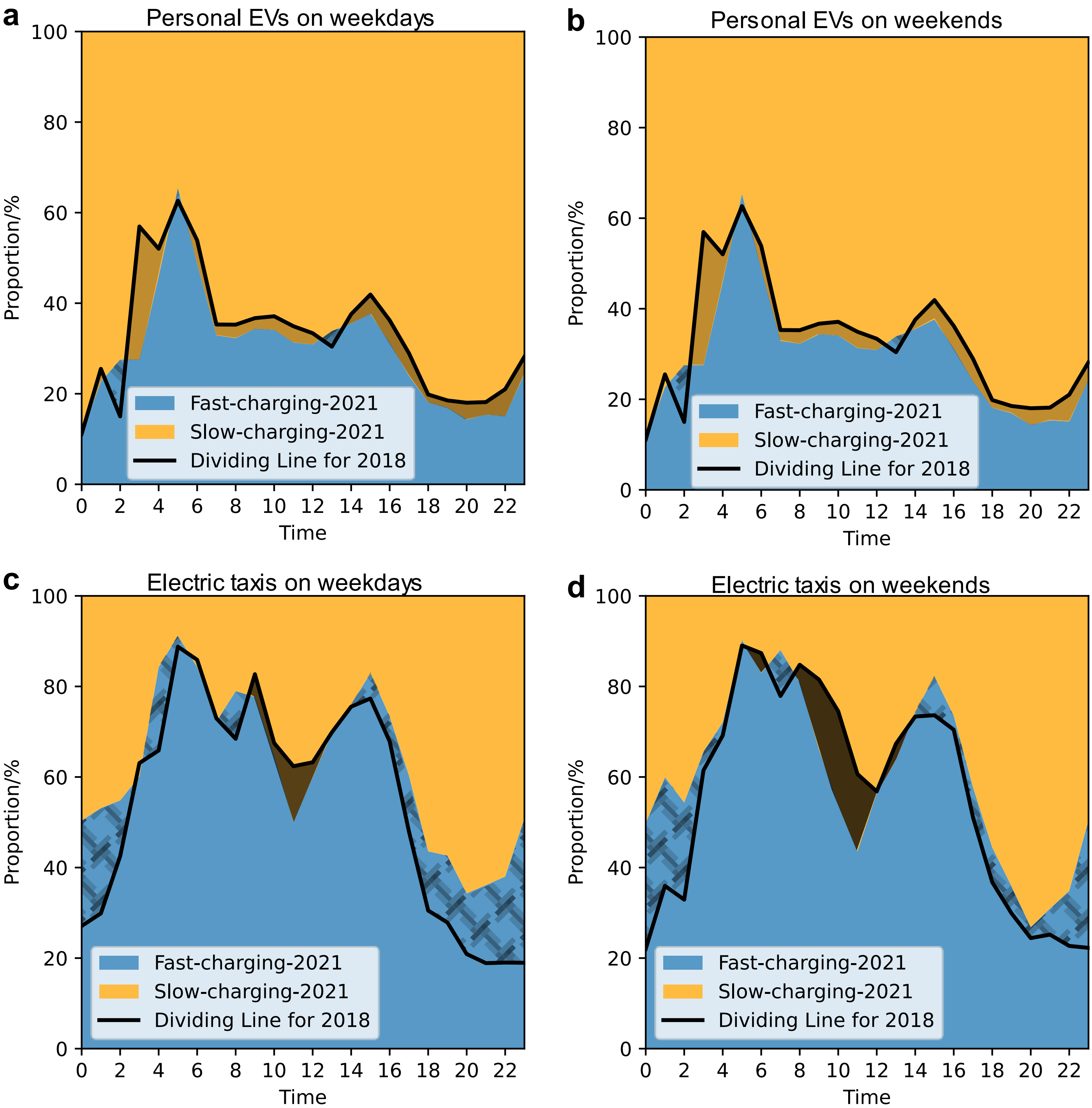

Fig.8. The plug-in time distribution of the charging method section proportion in 2018 and 2021. Personal EVs on **a** weekdays and **b** weekends; Electric taxis on **c** weekdays and **d** weekends.

5.3 Remaining Mileage when Charging

Differ from the results of initial battery charging SOC in Section 5.1, the remaining mileage at the start of charging is an absolute value. In previous studies, when considering assessing or analysing the range anxiety, some used SOC (Pevec et al., 2020; Zhang et al., 2021) while others used remain mileage (Yuan et al., 2018; Pevec et al., 2020; Rainieri et al., 2023) to reflect the user psychology. It is tight to determine which indicator can reflect the range anxiety more significantly. The distributions of the remaining mileage at the start of charging are provided in **Fig.9**. The statistical results of average and quartiles are shown in **Appendix E.**

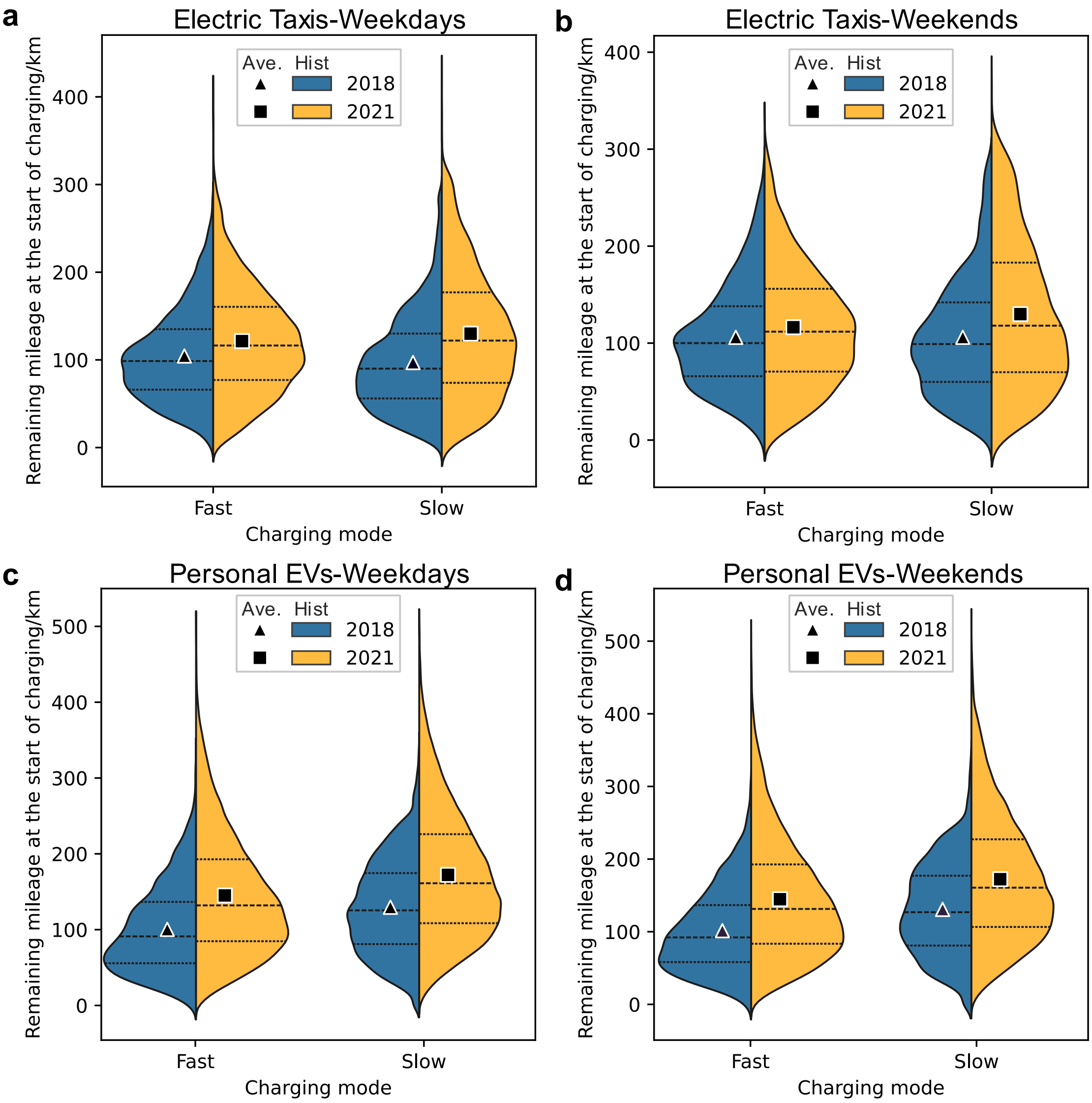

Fig. 9 Remaining mileage at the start of charging. Electric taxis on **a** weekdays and **b** weekends; Personal EVs on **c** weekdays and **d** weekends.

For electric taxis, the average value increases by around 10.1% of fast charging and 22.5% of slow charging on weekends (M-W U test, p<0.001). On weekdays, the increases are even higher, with fast charging rising by approximately 16.3% and slow charging by 33.3% (M-W U test, p<0.001). The growth rates of the first quartiles are lower than that of the third quartiles both on weekends and weekdays, illustrating that taxis with a higher remaining range might charge more frequently.

For personal EVs, the average remaining mileage when charging increases by 42.8% of fast charging and 32.0% of slow charging on weekends (M-W U test, p<0.001). This is different from the results of electric taxis, whereas higher growth in fast-charging behaviours than that in slow-charging behaviours. On weekdays, the situation is similar, that 45.0% increases in fast charging and 33.4% increase in slow charging (M-W U test, p<0.001). In terms of the shape of the distributions, there shows a quite high-proportion fast-charging first quartile of the remaining mileage in 2018. The values for all quartiles are significantly higher in 2021 but remain more concentrated in the first quartile.

6. Implication of Range Anxiety

6.1 Assessments

All in all, the purpose of enhancing AER and charging power is to improve usage confidence and experience of EV users. Range anxiety is the most important indicator affecting the development of EVs from the perspective of users. Therefore, we use initial battery SOC and remaining mileage when charging to assess the changes of range anxiety between 2018 and 2021. There two indicators are persuasive and always analysed in previous studies (Yuan et al., 2018; Pevec et al., 2019, 2020; Zhang et al., 2021; Rainieri et al., 2023;

Carbon and Gebauer, 2017; Shrestha et al., 2022). However, it still has some arguments about which one is much more suitable to be used in assessment. For instance, Rainieri et al. (2023) figured out that people are more influenced by the remaining driving range than the SOC when making decisions about how far they are willing to drive to reach another charging station. In contrast, Zhang et al. (2021) considered that battery SOC is the determining factor of the charging decision. Nevertheless, we assess these two indicators using ordinary least squares (OLS) algorithm (Zhang et al., 2021; L. Zhao et al., 2023a). The aim for this assessment is to describe the real-world situation and its changes rather than argue which indicator is more suitable to define the range anxiety, because it operates as a rhetorical construction that is neither purely technical nor psychological (Noel et al., 2019). The basic models for SOC and remaining mileage are provided as equations (1) and (2). The logarithm is used in this paper, because it can reduce the absolute value of the data to facilitate calculation and easily eliminate heteroskedasticity in the obtained data (Zhang et al., 2021).

$$\ln SOC_{i,y} = \alpha_0 \ln P_{i,y} + \beta_0 \ln AER_{i,y} + \gamma_0 X + \varepsilon_0 + \xi_0, i \in I, y \in Y \tag{1}$$

$$\ln RM_{i,y} = \alpha_1 \ln P_{i,y} + \beta_1 \ln AER_{i,y} + \gamma_1 X + \varepsilon_1 + \xi_1, i \in I, y \in Y \tag{2}$$

$$RM_{i,y} = SOC_{i,y} \times AER_{i,y} / 100, i \in I, y \in Y \tag{3}$$

where ln $SOC_{i,y}$ refers to the SOC of the i-th charging event in y-th year; ln $RM_{i,y}$ refers to the remaining mileage of the i-th charging event in y-th year. As the variables affecting range anxiety, we expect that more SOC and mileage left, the greater the user's anxiety. The relation between RM and SOC is provided in equation (3). ln $P_{i,y}$ represents the charging power of the i-th charging event in y-th year; ln $AER_{i,y}$ is the AER for the vehicle of the i-th charging event in the y-th year. X represents the control variables, including ln $CuM_{i,y}$, ln $DBS_{i,y}$, $Day_{i,y}$ and $Time_{i,y}$. α and β represent the regression coefficient. ε is the random error term, and ξ represents a constant term. Among the control variables, ln $CuM_{i,y}$ represents the natural logarithm of the total mileage for the vehicle of the i-th charging events in the y-th year. ln $DBS_{i,y}$ is the natural logarithm of the distance since last charge of the i-th charging events in the y-th year, which is analysed in Section 4.3. *Day* represents the charging event is on a workday or non-workday, which is in the line with the results in previous sections. *Time* is the plug-in time, which is analysed in **Section 5.1**.

The natural logarithm used in this model makes it to be interpreted as elasticity, i.e., implicit variable changes proportionally with independent variables. The results are provided in **Table 6**. According to equation (3), the difference between ln SOC and ln RM is in the terms of ln AER and constant, thus, ln P and other control variables are not provided in the results of ln RM.

Table 6 Results of initial battery charging SOC for regression analysis.

	Variables	Personal EVs		Electric taxi	
		y=2018	y=2021	y=2018	y=2021
ln SOC	ln P	-0.143***	-0.124***	0.012***	-0.055***
		(0.003)	(0.001)	(0.004)	(0.005)
	ln AER	0.202***	0.115***	0.344***	-0.059***
		(0.019)	(0.003)	(0.019)	(0.022)
	Day	0.001	0.045***	-0.017**	0.072***
		(0.006)	(0.002)	(0.007)	(0.010)
	ln CuM	-0.008***	-0.004***	-0.075***	-0.008**
		(0.002)	(0.001)	(0.004)	(0.006)
	ln DBS	-0.276***	-0.292***	-0.370***	-0.292***
		(0.004)	(0.001)	(0.004)	(0.005)
	Time	-0.146***	-0.156***	-0.307***	0.009
		(0.010)	(0.003)	(0.013)	(0.015)
	Constant	4.315***	4.763***	4.340***	5.478***
		(0.110)	(0.019)	(0.093)	(0.143)
ln RM	ln AER	1.202***	1.115***	1.344***	0.941***
		(0.019)	(0.003)	(0.019)	(0.022)
	Constant	-0.291***	0.158***	-0.266***	0.873***
		(0.111)	(0.018)	(0.093)	(0.143)

Note: (i) Entries in parentheses are standard error. (ii) *, **, *** indicate significant at the statistical level of 10%, 5% and 1% respectively.

In terms of personal EVs, charging power has a negative impact on the initial battery charging SOC both in 2018 (α=-0.143) and 2021 (α=-0.123). This result is same as the findings of previous studies emphasising that the increase of charging power can alleviate range anxiety are consistent (Zhang et al., 2021). Moreover, the regression coefficient on the AER in 2018 and 2021 shows a positive relation between AER and SOC, indicating that longer AER users will leave more SOC. The same trends are in the regression coefficient on the AER to RM. There is a change in correlation of electric taxis between 2018 and 2021. The regression coefficient on the charging power is 0.012 in 2018, while it changes into -0.055 in 2021, illustrating the initial charging SOC for electric taxis decreases with the increased charging power in 2021. The impact of AER on initial charging SOC is 0.344, while it also changes into negative (β=-0.059) in 2021. Considering the influence of AER on remaining mileage, the regression coefficient changes of electric taxis in 2018 and 2021 suggests that higher AER results in more remaining mileage left when electric taxi driver charging their vehicles.

6.2 Discussions

Based on the statistical results in this paper, the first notable observation is that charging power and AER have increased significantly in 2021. However, there have been only minor increases in average and maximum daily VKT on weekdays for personal EVs, despite a 50.8% rise in AER and a 13.9% increase in average charging power (see **Section 3**). Additionally, the distance between charges has only increased by 16.7%, which is much lower than the AER increase (see **Section 4.3**). Our findings suggest that current EVs can meet the daily travel demands of more than 99.5% of personal EV users in 2021 (see **Section 4.2**). However, compared to the 2009 survey results on ICEVs, Zhou et al., (2020) concluded that a 300-mile range is necessary to cover 90% of drivers' travel needs in Beijing. Based on the cumulative probability distribution of daily travel mileage for consumers in China, Liu et al., (2023) suggested that a 300-km range EV can satisfy 98.6% of people's daily travel scenarios. In contrast, the average AER of personal EVs in this study is only around 230 miles. The data analysed reflect the results under current AER constraints, meaning we are unable to assess users who typically drive longer daily VKTs with ICEVs. This indicates that high-intensity EV users remain relatively uncommon in our sample, inferring more EV usage in daily commuter scenarios (Cui et al., 2022). It should also be noted that with a higher AER, more battery materials are left idle. Our analysis shows about a 40% increase in idle materials in 2021 (combining the results on weekdays and weekends), based on the remaining mileage when users charge their vehicles. The increased use of battery materials could lead to more environmental pollution, especially in battery manufacturing and recycling processes (Nie et al., 2024). As a result, many studies have focused on determining the optimal AER for different EV users (Noel et al., 2020; Zhou et al., 2020, 2023). Increasing battery capacity also raises costs, potentially affecting users with lower usage intensity (Liu et al., 2023; Yang, 2022; Zhou et al., 2023). In contrast, the effect of increased AER and charging power on electric taxis has been relatively obvious. A 26.5% increase in AER and a 29.9% increase in charging power are observed alongside approximately a 15.2% rise in daily VKT (see **Sections 3 and 4**). Around 48% of electric taxi users can meet their daily travel demands with the vehicle's battery capacity (average AER is about 177 miles). This is lower than the finding that electric taxis with a 220-mile range can meet the needs of about 90% of drivers (Zhou et al., 2020). However, the gap in daily VKT between electric- and traditional taxis has been narrowing, though a difference of around 100 km remains (Hao et al., 2020). Nevertheless, batteries store energy through chemicals, while fuel tanks do not convert energy by being mere containers themselves. If the battery is designed for excessive mileage, like a fuel tank, then the balance among material usage rate, cost and energy consumption need to be well thought out (Meinrenken et al., 2020).

Another issue discussed in this paper is range anxiety. Based on the study results, it is evident that increasing charging power has a greater effect on mitigating range anxiety than extending the AER (see **Section 6.1**). A longer AER results in drivers charging their vehicles with more remaining mileage, and the initial battery charging SOC has shown only slight variation between 2018 and 2021. This doesn't mean that longer AER will lead to more range anxiety, however it is consistent with previous research suggesting that charging technology is more effective at alleviating users' range anxiety than gains in AER (Melliger et al., 2018; Shrestha et al., 2022; Liu et al., 2023). Therefore, it may be inferred that remaining SOC is more suitable for assessing range anxiety because the hypothesis of more AER will bring less remaining mileage is not true. The convenience and availability of more charging options may give users greater confidence in using their vehicles without worrying about running out of charge, such as more public charging stations, private charging piles and higher charging power (see **Sections 3.2 and 5.2**). Unlike traditional refueling behavior, where the filling stations are not spread throughout every neighbourhood and street, charging infrastructure offers more frequent opportunities to replenish energy. For instance, in Beijing, the number of public charging stations increased from 2,100 in 2018 to 5,850 in 2021, and the number of charging piles rose from 21,100 to 96,000. According to Beijing's 14-th Five-Year Plan, 60% of new EVs should be accompanied by supporting personal charging facilities. While we couldn't find 2018 data for comparison, it can be believed that, with policy support, the 2021 figures are certainly higher than those of 2018. Therefore, although AER has increased, the results of distance between two charges and SOC distributions suggest that users are not waiting until their batteries are fully depleted before charging. This is likely because they now have more opportunities to charge their vehicles both spatially and temporally.

7. Conclusions

Based on a large-scale real-world EV operation data in Beijing, this paper provides an in-depth understanding of EV travel habits and plug-in habits between 2018 and 2021. In these two different years, the AER of personal EVs increases about 50.8%and the results of electric taxis increases about 26.5%. Besides, charging power also has a 13.9% increase for personal EVs, while it increases more for electric taxis, about 29.9%. Compared to the vehicle technology and charging technology in 2018, it has a significant improvement in 2021. In the condition of possible less charging duration and longer travel distance, we find that the daily VKT of electric taxis increase by 13.5% on weekdays and 17.1% on weekends. However, there only about 7.9% increase of personal EVs in weekdays. Moreover, the maximum daily VKT of personal EVs can be covered by the AER without a charge in 2021, while this value is about 98% in 2018. It shows a more battery utilisation of electric taxis in 2021. In terms of distance between two charges, there are both a few increases for personal EVs (16.7%) and electric taxis (20.0%). However, the results of SOC between two charges of electric taxis are not significant, and it shows a 9.1% reduction in personal EVs. In terms of charging habits, more concentrated distribution of the slow-charging plug-in time around 6 p.m. to 8 p.m. is observed both on weekday and weekends in 2021 than that in 2018. The average slow-charging plug-in battery charging SOC of personal EVs reduce about 2.0% on weekdays and weekends, while the average fast-charging initial SOC increases 2.0% on weekdays between 2018 and 2021. Charging time distributions of electric taxis has changed a lot between 2018 and 2021. The average of slow-charging increases approximately 2.6% on weekdays, while the average of fast-charging reduces about 2.0% on weekends. The remaining mileage before charging for both personal EVs and electric taxis has increases significantly. Finally, the results also indicate that as charging power increases, there is a significant decline in range anxiety calculated by the state-of-charge before charging (rather than remaining mileage before charging), a trend not observed with increasing AER.

There are some limitations of this paper, including:

1. User attributes are important for assessing the range anxiety, which is always collected from traditional questionnaires. However, limited by the collection path, the EV data has not been matched with user information. If it is possible to combine data-driven method with survey in the future, the results can be more abundant and detailed. For example, analysing user behaviour based on different attributes such as age, income, or driving experience could provide valuable insights into how various demographic groups experience and manage range anxiety. This approach would enable a more tailored understanding of user behaviour, potentially improving the design of charging infrastructures and EV features to better meet diverse user demands.
2. During the SOC and mileage calculation, the battery aging was excluded because we cannot require the true real-time battery capacity. Battery health estimation is a complex process. Although we considered cumulative mileage of EVs, these errors may still affect vehicles with a long total distance. The impact of battery state-of-health on behaviour changes can be considered in future studies. An accurate battery health estimation model could be integrated into the range anxiety assessment model to provide more reliable insights into how battery degradation influences range anxiety and usage patterns over time.

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Appendix. A. Raw operating data example.

Table A.1 Raw operating data example of an EV.

Timestamp	Velocity (km/h)	Mileage (km)	Battery SOC (%)	Battery pack voltage (V)	Battery pack current (A)	Vehicle state
2021-03-02 19:03:47	33.6	137,021.0	65.0	336.2	15.8	Driving
2021-03-02 19:13:47	39.9	137,021.0	65.0	336.5	3.1	Driving
2021-03-02 19:13:57	42.7	137,021.0	65.0	338.0	-38.6	Driving
2021-03-02 19:14:07	37.2	137,021.0	65.0	336.4	8.1	Driving
2021-03-02 19:14:17	42.2	137,021.0	65.0	337.1	-11.7	Driving
…	…	…	…	…	…	…
2021-03-02 20:20:06	0.0	137,053.0	55.0	328.6	-9.2	Charging
2021-03-02 20:20:16	0.0	137,053.0	55.0	328.7	-9.2	Charging
2021-03-02 20:20:26	0.0	137,053.0	56.0	328.7	-9.2	Charging
2021-03-02 20:20:36	0.0	137,053.0	56.0	328.7	-9.2	Charging
2021-03-02 20:20:46	0.0	137,053.0	56.0	328.8	-9.2	Charging
…	…	…	…	…	…	…

Appendix. B. Charging Power.

Charging power is calculated by battery voltage and battery current. Real-time charging power can be calculated using the multiple between voltage and current. Due to these two parameters will be changing during the charging process, and the total charging power will show a reduction trend. Therefore, in order to recognise what kind of charging is, the average charging power in first 10 timeframes are used to determine the charging power selection. If the value is more than 10 kW, it will be determined as a fast-charging process; vice versa. The calculation should be followed by equation (s.1).

$$\text{Ave}P=\sum_{t=10} U_t I_t dt \tag{s.1}$$

where P is the charging power, kw; U is the battery voltage at timeslot t, V; I is the battery current at timeslot t, A.

Appendix. C. Daily Vehicle Kilometre Travelled.

VKT is an important indicator to assess the intensity of the vehicle usage. It can be divided into different time dimensions, while daily VKT is used to analyse the daily mobility of EV users. Based on the statistical dataset for EVs in Table IV, all driving events should be integrated into a daily dimension. This process should be followed by equation (s.2) – (s.3).

$$\text{daily } VKT_{v,i} = \sum_{n\in N} \text{d}_n^{trip} \left(\text{state}_n\text{=drving}\right), i \in I \tag{s.2}$$

$$\text{max-daily} VKT_v = \max\left(\text{daily} VKT_{v.i}\right), i \in I \tag{s.3}$$

where *daily* $VKT_{v,i}$ is the result of the v^{th} EV in the i^{th} day, km; I is statistical period with the index of the day i; d^{trip} is the n^{th} segment with the state of driving, km; *Max-daily* VKT_v is the maximum daily VKT of the v^{th} EV in the whole period (i.e., one month in this paper), km.

Appendix. D. Battery Utilisation Rate.

The calculation method of the BUR can be found in the paper proposed by Zhao et al., 2021. It can be used to assess the battery material waste of EVs. The calculation should be followed equation (s.4). Considering the maximum BUR (Max-BUR), the calculation method can be changed into equation (s.5), which is used in this paper.

$$BUR_{v,i} = daily VKT_{v,i} / \text{AER}_v \tag{s.4}$$

$$\max\text{-}BUR_v = \max\text{-daily} VKT_v / \text{AER}_v \tag{s.5}$$

where BUR is the result of the v^{th} EV in the i^{th} day, %; max-BUR is the maximum result of the v^{th} EV, %.

Appendix. E. Statistical results.

Table E.1 Statistical results of the daily VKT for electric taxis and personal EVs on weekdays and weekends in 2018 and 2021.

Scenario	Day	Year	Average/km	First quartile/km	Median/km	Third quartile/km
Personal	Weekend	2018	44.8	25.5	38.7	56.8
		2021	44.7	24.6	38.7	57.0
	Weekday	2018	39.5	22.3	33.5	49.4
		2021	42.6	23.3	36.3	54.2
Taxi	Weekend	2018	119.1	83.0	116.4	152.2
		2021	139.5	79.0	133.2	187.5
	Weekday	2018	132.5	100.5	130.0	164.4
		2021	150.3	91.7	144.7	204.4

Table E.2 Statistical results of the distance (battery utilisation rate) between two charges for electric taxis and personal EVs in 2018 and 2021

Scenario	Year	Average/km (%)	First quartile/km (%)	Median/km (%)	Third quartile/km (%)
Personal	2018	131.9 (51.2)	103.5 (40.4)	130.4 (50.6)	159.8 (61.7)
	2021	153.9 (42.1)	108.3(31.6)	146.4 (40.9)	191.5 (51.4)
Taxi	2018	113.7 (50.1)	93.5(41.0)	114.2 (49.2)	132.6 (58.4)
	2021	136.5 (49.5)	112.3 (41.2)	131.1(48.9)	156.9 (57.3)

Table E.3 Statistical results of remaining mileage at the start of charging of electric taxis in 2018 and 2021

Day	Mode	Year	Average/km	First quartile/km	Median/km	Third quartile/km
Weekend	Fast	2018	105.9	65.8	100.0	138.0
		2021	116.3	70.6	111.8	156.0
	Slow	2018	105.9	60.0	99.0	142.0
		2021	129.8	70.0	118.0	183.0
Weekday	Fast	2018	104.4	66.0	98.7	135.0
		2021	121.4	77.0	116.4	160.5
	Slow	2018	97.0	56.0	90.0	130.0
		2021	129.9	73.8	122.0	177.0

Table E.4 Statistical results of remaining mileage at the start of charging of personal EVs in 2018 and 2021

Day	Mode	Year	Average/km	First quartile/km	Median/km	Third quartile/km
Weekend	Fast	2018	101.4	58.2	92.2	136.6
		2021	144.7	83.5	131.4	192.7
	Slow	2018	130.8	81.0	126.9	177.1
		2021	172.3	106.6	160.6	227.2
Weekday	Fast	2018	100.3	55.6	91.1	136.6
		2021	145.1	84.7	132.0	192.8
	Slow	2018	129.6	80.9	125.4	174.5
		2021	172.3	108.5	161.2	225.9