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REGULAR PAPER

When mobility on demand meets vehicle electrification: a longitudinal study on evolution of city-scale ridesharing

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Abstract
With the rapid development of ubiquitous computing, our society is witnessing a rapid expansion of mobility-on-demand services, in which ridesharing (e.g., Uber, Lyft, and DiDi) has become one of the most successful applications and has percolated into people's daily life. Even though a large number of research studies have been conducted to understand the demand and supply patterns or improve the operation efficiency of ridesharing services, little is known at a comprehensive level on their evolution, especially during the widely-initiative vehicle electrification process that electric vehicles start to take over conventional gas vehicles gradually. Different from conventional gas vehicles, electric vehicles have some unique characteristics, e.g., long charging time compared to the refueling process of gas vehicles, which potentially makes a difference in providing ridesharing services. In this paper, we seek to shed light on the evolution of city-scale ridesharing services with the penetration of large-scale electric vehicles. In particular, our study is based on a ridesharing operation dataset from the Chinese city Shenzhen in 2019, including all orders served by over 50,000 unique ridesharing drivers. We perform a set of observations on the differences between gas vehicle and electric vehicle drivers for ridesharing services from different dimensions, e.g., spatial, temporal, and income, etc. Our study shows that understanding the evolution of city-scale ridesharing with the penetration of electric vehicles has strong implications for ridesharing drivers, passengers, operators, and city governments. On the one hand, our findings paint a promising picture of electric vehicles for ridesharing services, showing its prosperity in the Chinese city Shenzhen. On the other hand, our study also has the potential to provide some meaningful guidelines for other cities that plan to replace their vehicles for ridesharing services with electric vehicles based on the obtained insights, e.g., possible drawbacks for long trips and charging infrastructure deployment.

Keywords Sharing mobility · Ridesharing service · Electric vehicle · Evolution

1 Introduction

Due to the prevalence of smartphones and ubiquitous mobile devices, in the past decade, we have been witnessing an explosion of mobility-on-demand services (He and Shin 2019), including bikesharing (Wang et al. 2019a; He and Shin 2020b), carsharing (Wang et al. 2021a, 2020b), e-scooter sharing (He and Shin 2020a), and ridesharing (e.g., Uber, Lyft, and DiDi (Xu et al. 2020; Li et al. 2019)). At the same time, with the ever-increasing concerns over air pollution, we are also witnessing a rapid vehicle electrification process since electric vehicles (EV) are considered as a cleaner alternative to conventional gas vehicles (GV) (Zhang et al. 2021; Wang et al. 2020d; Du et al. 2018), e.g., zero tailpipe emissions of EVs, which motivates many cities around the world to replace their ridesharing GVs with EVs. For example, Uber and Lyft (Walz 2019; SASHA LEKACH

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2019) are accelerating the electrification of ridesharing vehicles, and Uber has announced a new goal to electrify its entire London fleet by 2025 (Vincent 2017).

Even though there is an increasing number of studies on different aspects of ridesharing services, e.g., competition and accessibility (Jiang et al. 2018), labor issues (Glöss et al. 2016), and order dispatching (Zhang et al. 2017; Lin et al. 2018), most of them focused on conventional GVs. To our knowledge, little work has been done to investigate the penetration of EVs into ridesharing services during the evolution process. However, EVs are typically different from GVs due to their long charging time (e.g., it usually takes over 2 h for EV drivers to fully charge their vehicles even using the fast chargers, while the refueling processes of GVs typically last for 3–5 min (Wang et al. 2019b), which potentially limits EVs' operation time, resulting in low supply and accessibility of ridesharing vehicles. Therefore, it is necessary for us to understand the comprehensive evolution patterns (e.g., driver profit and passenger waiting time) of city-scale ridesharing during its electrification process.

To reveal the unseen, in this paper, we conduct the first longitudinal study on the evolution of city-scale ridesharing services during the EV penetration process. We seek to shed light on the evolution of ridesharing services in the Chinese city Shenzhen, which has, to our knowledge, the largest electric ridesharing fleet in the world. Specifically, our measurement study has three key features: (i) *a long data collection period*, including all ridesharing order records from January 2019 to September 2019 in Shenzhen; (ii) *a large number of vehicles* for ridesharing services (e.g., over 50k vehicles), and the number of EVs for ridesharing has significantly increased from 8k to 24k during the nine months; (iii) *a large number of user trip records*, e.g., more than 165 billion ridesharing trips. We first utilize the dataset to show the evolution of the number of EVs and GVs (Sect. 2.4). Then we explore the spatiotemporal evolution of electric ridesharing (Sect. 3). Next, we extensively investigate the impacts of ridesharing EV penetration on drivers (Sect. 4), passengers (Sect. 5), and society (Sect. 6) with different metrics. Finally, we report a set of findings and insights obtained from our investigation, combined with some discussions about potential implications (Sect. 7). Among all observations and insights, we provide some of the most prominent below, and more details will be shown in the paper.

- *Income* EV drivers typically have higher daily income than GV drivers due to longer operation distance and time, but almost all long trips (e.g., cross-city trips) are served by GVs.
- *Driver age* The newly registered ridesharing drivers are more likely to be young EV drivers. Middle-aged drivers have the longest average daily operation time, distance, and income compared to drivers of other ages.
- *Driver gender* The average daily operation time of female drivers is longer than that of male drivers, but the number of regions they operate is less than male drivers on average.
- *Passenger waiting time* With more EVs penetrating into the ridesharing services, passengers are more vulnerable to longer waiting time when there are too many concurrent orders. Passengers' waiting time has a strong correlation with the difference between the number of orders and the number of ridesharing EVs.
- *Societal impact on CO_2 reduction* Ridesharing EVs have a huge potential to reduce the CO_2 emissions, e.g., the ridesharing EVs in Shenzhen reduced 1.17×10^7kg CO_2 emissions in September 2019.

To the best of our knowledge, this is the first comprehensive longitudinal study on EV penetration into ridesharing services at the city scale. We believe that our efforts and the revealed insights have the potential to benefit the research community, as well as city governments, ridesharing operators, and drivers.

2 Dataset and statistics

In this section, we introduce the operation of ridesharing systems, datasets that we will use throughout this paper, as well as some preliminary analysis.

2.1 Ridesharing operation

Figure 1 shows the general ridesharing operation paradigm. Different roles (user/passenger, driver, and operator) are interacted with each other to invigorate the urban mobility dynamics.

- *Users/passengers* need to sign up as a user role via mobile Apps provided by operators before the first-time use of ridesharing services. Each ridesharing operator

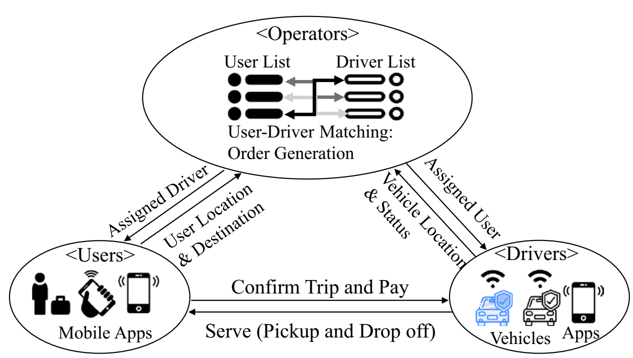


Fig. 1 Ridesharing operation

provides its own App for users, e.g., Uber, Lyft, and DiDi. The original locations and time and expected destinations (i.e., OD) of users are required for sending a ride request through an App, and these request records are then uploaded to the ridesharing data center through network connections for responding.

- *Drivers* need to sign up as a driver role via mobile Apps if they want to be ridesharing drivers, and their demographic information (e.g., age and gender) is needed for security purposes. The real-time location (i.e., vehicle GPS coordinates) and status information (i.e., available or not) of drivers are also periodically uploaded via communication devices and then stored in the servers for management and analysis.
- *Operators* provide operation management services (e.g., order dispatching) for all registered drivers and users via centralized ridesharing management platforms. After receiving ridesharing requests from users in a short duration, the management platform will match these users to the optimally available drivers by batching matching. The dispatching decisions will be sent to drivers and users once they are matched. EVs and GVs are equally treated when making scheduling decisions. After completing a trip, a complete ridesharing record will be generated, including user and driver information, as well as transaction information.

2.2 Data description

In total, our dataset includes ridesharing data in Shenzhen in 2019, which includes over 165 million records of more than 50,000 ridesharing vehicles. The details of our datasets are shown below:

- *Ridesharing order data* Each order record consists of fields describing vehicle and driver information, and transaction information, e.g., the order ID, order time, pick-up time, pick-up GPS coordinates (i.e., longitude and latitude), drop-off time, drop-off GPS coordinates, trip length, vehicle ID, EV flag, age and gender of drivers, etc.
- *Contextual data* In addition to the two main ridesharing data, we also leverage various contextual data for this longitudinal study, e.g., urban partition data provided by the Transport Commission of Shenzhen and weather data.

2.3 Data cleaning and management

Due to the long-term and large-scale ridesharing data, we made a lot of efforts in the data cleaning processes, e.g., data masking, map matching, and errant data filtering. We utilize an 80 TB Hadoop Distributed File System (HDFS) on a cluster consisting of 20 nodes to manage the data. For daily data processing, we utilize the MapReduce-based Pig and Hive since our analyses are based on historical log data, instead of streaming data.

Based on the cleaned large-scale dataset, we investigate the impacts of ridesharing evolution with EV penetration on different roles (e.g., driver and passenger) by defining various quantification metrics from different dimensions (e.g., spatial, temporal, and income). In addition, we also take the demographic information of ridesharing drivers (e.g., age and gender) into consideration.

2.4 Vehicle count evolution

Figure 2 shows the evolution of the number of EVs and conventional GVs in Shenzhen from January 2019 to September 2019. We found that the number of EVs has significantly increased during the nine months, from 8676 (17.9%) to 24,663 (42.5%), while the number of GVs has gradually decreased, from 39,766 to 33,381. We depict the evolution trend of EVs using a linear distribution with the coefficient of determination $R^2 = 0.9931$, as shown below:

$$\mathcal{N}_{EV}\left(Y_M\right) = 2085 \cdot Y_M + 5944.1 \tag{1}$$

$\mathcal{N}_{EV}$ is the number of EVs. Y_M is the month of the year, and Y_M starts from Jan 2019, which means Jan 2019 is 1 in Eq. 1.

After we fit the number of GVs in different functions, we found the Cubic function with $R^2 = 0.9565$ and Root Mean Square Error $RMSE = 521.1$ would be a superb choice, as shown below:

$$\mathcal{N}_{GV}\left(Y_M\right) = -22.16 \cdot {Y_M}^3 + 376.7 \cdot {Y_M}^2 - 2533 \cdot Y_M + 415500 \tag{2}$$

With the two distributions describing the evolution of the number of EVs and GVs, it is expected that the number of EVs will exceed GVs since November 2019.

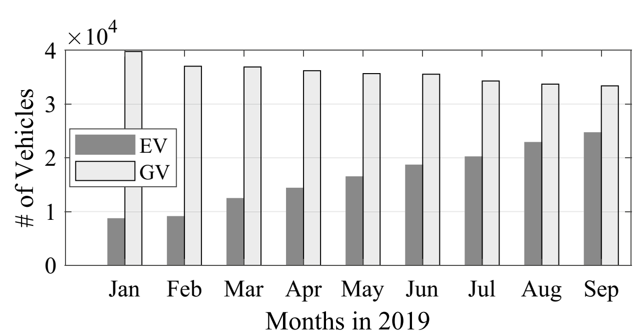


Fig. 2 Evolution of the # of EVs and GVs in Shenzhen

3 Spatiotemporal evolution

In this section, we investigate the spatiotemporal evolution of ridesharing orders during the EV penetration process.

3.1 Temporal evolution

Figure 3 shows the evolution distributions of average served order ratios by EVs and GVs in 24 h of a day. We have following observations:

(i) In January 2019, the percentage of served orders by GVs (79.1%) is much higher than that of EVs (20.9%), with 384,562 (GV):101,610 (EV) orders each day on average. From January to September, the supply gap between GVs and EVs becomes smaller and smaller, and the served order ratio becomes 52%:48%, with 393,679 (GV):363,396 (EV) orders each day on average. In some hours of September, e.g., 19:00–21:00, the percentage of served orders by EVs actually exceeds that of GVs, which may suggest the *EVs have the potential to take over the GVs for ridesharing services*.

(ii) The served order distributions of EVs and GVs (shape of curves) are similar from January to September, which potentially indicates that operators dispatch the vehicles to serve passengers without considering they are EVs or GVs (we verified this with operators in Shenzhen), so passengers cannot decide the serving vehicle types (i.e., EVs or GVs).

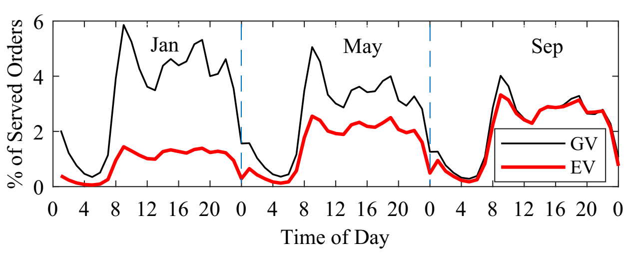


Fig. 3 Evolution of order distribution in 24 h of a day

(iii) During the evolution process, we found the largest gap between served orders by EVs and GVs happens during the morning and evening rush hours (i.e., 9:00–10:00 and 18:00–19:00). The reason behind this phenomena would be there are both higher ridesharing demand and supply during the rush hours, as we found there are some part-time ridesharing drivers who only provide rides for passengers when they go to work or come back to home from work, while most of those private cars are GVs.

3.2 Spatial evolution

We leverage the urban partition data of Shenzhen to investigate the spatial evolution of EV drivers for ridesharing services. There are 491 regions in Shenzhen based on the partition of the Shenzhen government. We define the *spatial ratio* $\mathcal{SR}$ to investigate the served order distributions by EVs and GVs, which is the number of orders served by EVs or GVs divided by the total orders in each region in one day. Equation 3 shows the *spatial ratio* $\mathcal{SR}$ of EVs in region $\mathcal{X}$, where $\mathcal{NO}_{EV}(\mathcal{X})$ is the number of orders served by EVs in region $\mathcal{X}$ and $\mathcal{NO}_{all}(\mathcal{X})$ is the total number of orders in region $\mathcal{X}$.

$$\mathcal{SR}(\mathcal{X}) = \frac{\mathcal{NO}_{EV}(\mathcal{X})}{\mathcal{NO}_{all}(\mathcal{X})} \tag{3}$$

Figure 4 shows the $\mathcal{SR}$ of EVs in each region during the evolving process of the Shenzhen ridesharing services, where the darker red areas means there are low $\mathcal{SR}$ of EVs in these regions, and the lighter yellow areas indicate more orders are served by EVs in these regions compared to GVs. In addition to the qualitative visualization, we also quantitatively show the $\mathcal{SR}$ distributions in all the 491 regions, which can be seen from the upper right corner of the figure. According to Fig. 4, we have the following observations:

(i) The $\mathcal{SR}$ of EVs have significantly increased from January 2019 to September 2019, which may be mainly caused by the penetration of large-scale EVs into the Shenzhen ridesharing services during this period, e.g., the number of EVs for ridesharing ser-

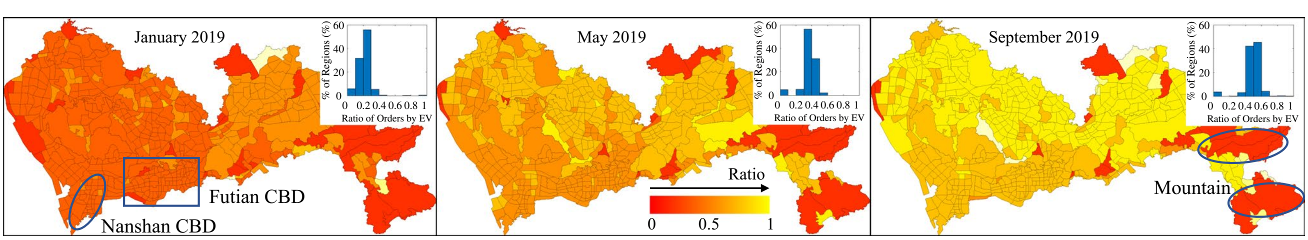


Fig. 4 A visualization of the evolution of the served order ratios by EVs in 491 regions of Shenzhen

vices has tripled from 8676 to 24,663 during the nine months.

(ii) A **surprising finding** is that almost all regions of high $\mathcal{SR}$ of EVs are in the suburban areas (e.g., non-CBD area), and this phenomenon is persistent during the EV penetration process. There is a rapid increase of the $\mathcal{SR}$ of EVs, and more orders are served by EVs in the suburban areas compared to the GVs. One possible reason is that the heavy traffic jams in urban Central Business District (CBD) areas will accelerate the energy consumption of EVs, so drivers prefer to use EVs for ridesharing services in suburban areas to prolong their daily operation time. Another reason could be there are more charging stations deployed in the suburban areas, so EV drivers are easier to charge their EVs in those areas.

(iii) Quantitatively, the $\mathcal{SR}$ of EVs in 93.7% of regions is not larger than 0.3 in January, which suggests the ridesharing market in January is dominated by GVs in Shenzhen. In May, the $\mathcal{SR}$ of EVs in about 88% of regions is between (0.4-—0.6], which means the EVs and GVs have a similar ridesharing share at this time. In September, we found that the *service ratios* of EVs in 92.7% of regions are over 0.5, which means EVs have more orders than GVs in almost all regions in Shenzhen, and they are dominating the Shenzhen ridesharing market. *In summary, Shenzhen has experienced a rapid ridesharing market transition in the nine months, from the GV-dominating market to an EV-leading one.*

3.3 Order entropy evolution

Since the order pickup (i.e., origin) locations indicate where the ridesharing drivers are willing to go and provide rides for users, we define the *Order Entropy* to quantitatively measure the operation activity range of each individual driver, which is denoted as below:

$$H(O) = -\sum_{r_i \in \mathcal{R}} p(r_i) \log_2 p(r_i) \tag{4}$$

Where $H(O)$ is the *Order Entropy* of the ridesharing driver in a time period (e.g., one month, one week, or one day). $\mathcal{R}$ is a region set, which includes all regions that the driver provides rides for users. $p(r_i)$ is the probability of served orders by the driver in the region r_i and $r_i \in \mathcal{R}$.

Since we found there is no much difference during the nine months for the *Order Entropy* distributions, we utilize all data to compare the *Order Entropy* distributions of EV drivers and GV drivers, which is shown in Fig. 5. We found the EV drivers typically operate in more regions than GV drivers, e.g., more than 72% of EV drivers operate in more than 16 regions on average (*Order Entropy*>4), while only about 53% of GV drivers operate in more than 16 regions on average. This observation indicates that the EV model may not limit the activity regions of drivers to provide ridesharing services within the city, and we also found about 75% of rides are shorter than 10 km.

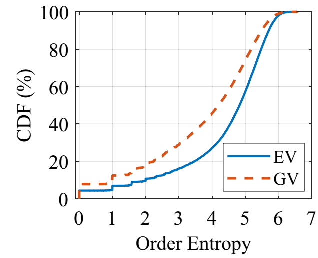


Fig. 5 Order entropy of EV and GV drivers

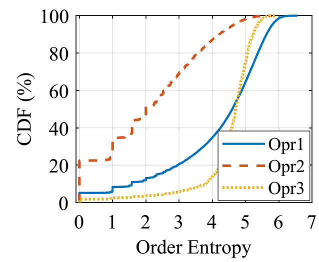


Fig. 6 Order entropy of drivers of three operators

We also compare the *Order Entropy* distributions of ridesharing drivers belonging to the three major operators in Shenzhen, as shown in Fig. 6. We found that the drivers of *Operator 3* normally operate in more regions to serve passengers, e.g., about 95% of *Operator 3's* drivers serve passengers in more than 8 regions (*Order Entropy*=3) on average, while about 79% of drivers of *Operator 1* and 32% of drivers of *Operator 2* operate in more than 8 regions on average. About 66% of drivers in *Operator 2* operate in 2 regions (*Order Entropy* = 1) to 16 regions (*Order Entropy* = 4), while most drivers in *Operator 1* (i.e., 67%) and *Operator 3* (i.e., 86%) operate in 16 regions to 64 regions on average. We also found that the drivers with the highest activity range (*Order Entropy* > 6) are almost in *Operator 1*. Even though there may be different possible reasons behind this phenomena, (e.g., different operators have a different number of vehicles and different operation policies, drivers' preference), *we can conclude that EVs have the potential to operate and serve passengers in different regions, and it implies the range limitation of EVs may not hinder their daily operation in most cases.*

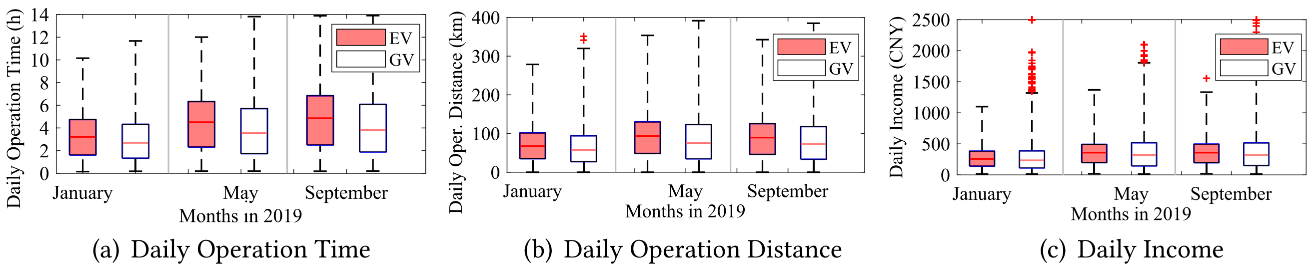


Fig. 7 Comparisons of daily operation time, daily operation distance, and daily income of EV drivers and GV drivers

4 Impacts on drivers

In this section, we investigate the impact of the evolution of ridesharing services with EV penetration on drivers' daily operation time, distance, and income. In addition, we also study the impacts on drivers with different demographic features.

4.1 Evolution of time, distance, and income

In Fig. 7, we compare the daily operation time, distance, and income of EV drivers and GV drivers during the evolution process.

From Fig. 7a, we surprisingly found that the 25th, 50th, and 75th percentiles of EVs are always larger than that of GVs from January to September, which means EV drivers typically operate longer time than GV drivers. This finding is counter-intuitive since we usually think EVs need a longer time for charging than refueling of GVs, so EVs should have shorter operation time. One possible reason may be that the newly registered full-time drivers must use EVs to provide ridesharing services and more existing ridesharing drivers replace their GVs with EVs. The longest operation time of GVs is always longer than that of EVs from January to September, but the gap becomes smaller with more EVs penetrating into the ridesharing services. One reason may be that there are more new EV models that have large battery capacities introduced to the ridesharing market, which potentially indicates that EVs have the potential to take over GVs for ridesharing services with the development of battery technologies.

A similar pattern is drawn from Fig. 7b, i.e., EV drivers typically operate longer distances than GV drivers. However, the maximum daily operation distance of EVs is always shorter than that of GVs. The possible reason is that the restricted battery capacity and the long charging time of EVs make them challenging to provide very long trips, e.g., cross-city trips. *We found 93% of trips longer than 150 km are served by GVs and 100% of trips longer than 200 km are served by GVs. Therefore, we argue that the current ridesharing EVs are hard to fulfill very long trips, so they cannot entirely replace GVs under current settings.*

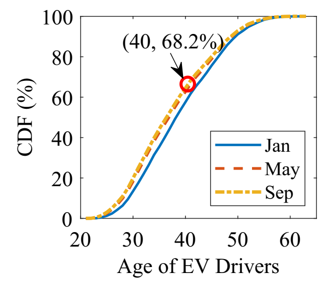


Fig. 8 Age distribution of EV drivers

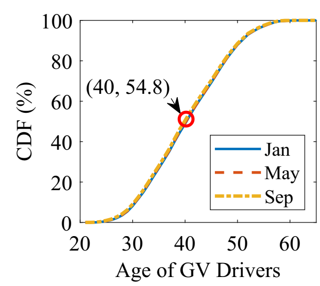


Fig. 9 Age distribution of GV drivers

With the above findings, it is not surprising that some GV drivers have very high daily income, which cannot be achieved by EV drivers due to the battery limitation. However, in general, most EV drivers have higher daily income than GV drivers since they operate for a longer time.

4.2 Age related evolution

4.2.1 Age evolution of ridesharing drivers

Figures 8 and 9 show the age distributions of EV drivers and GV drivers during the evolving process. We found the youngest driver is 20 years old, and very few drivers are over 55 years old, e.g., about 1.7% of EV drivers and 2.9% of GV drivers are over 55. Nearly half of the drivers (48.3%

of EV drivers and 45.2% of GV drivers) are between 30 and 40 years old.

(i) From January to September 2019, the ratio of young EV drivers with age under 40 has increased from 61.7% to 68.2%, while the counterpart of GV drivers has not change much during this period, which potentially indicates that more young drivers have registered as ridesharing drivers with their EVs.
(ii) Comparing the age distributions of EV drivers and GV drivers, we found that the EV drivers are younger than GV drivers since 68.2% of EV drivers are under 40 years old, but only 54.8% of GV drivers are under 40. One possible reason would be that young people are easier to overcome the disadvantages of EVs caused by their long charging time and accept EVs, while elderly drivers are more conservative and prefer to utilize GVs for ridesharing services.

4.2.2 Comparison of drivers in different age groups

We empirically divide the drivers into different groups using five-year-old as the slot. Then we utilize two statistical indicators (i.e., Mean and standard deviation (i.e., std)) to compare the daily operation time, distance, income, and *order entropy* of EV drivers and GV drivers in different age groups.

As shown in Table 1, we found both the Mean and std of daily operation time of GV drivers in all age groups are small than that of EVs, which means EV drivers usually operate a longer time than GV drivers. In addition, both EV drivers and GV drivers in 45–59 have the longest daily operation time than drivers in other age groups. One possible reason could be that most ridesharing drivers in this age range are full-time ridesharing drivers, and they need to work a long time to make a living.

We found that the average daily operation distance of EV drivers is longer than that of GV drivers for all age groups, while the std of GV drivers is larger than that of EV drivers, which indicates that EV drivers usually operate longer distances than GV drivers and have a small deviation in the same age group. The EV drivers in 50–59 have the longest daily operation distance, but the corresponding GV drivers are in 45–49.

For the daily income, we found that both EV drivers and GV drivers in 45–59 have the highest daily income from serving ridesharing passengers than drivers in other age groups, and the average daily income of EV drivers in senior age groups (over 50) is higher than that of GV drivers in the corresponding age groups. However, we found that the std of GV drivers is larger than corresponding age groups of EV drivers between 20–59, which potentially indicates that EVs cannot operate very far distance to earn a very high income.

We also compare the *Order Entropy* of EV drivers and GV drivers, and we found that EV drivers in 25–59 have larger *Order Entropy* and std, which means EV drivers in almost all age groups operate in more regions than GV drivers in corresponding groups. And the elderly drivers have higher *Order Entropy* than young drivers.

4.3 Gender related evolution

We also investigate the differences between male drivers and female drivers. From January 2019 to September 2019, we found both the number of male drivers and female drivers increased.

We found there are no obvious changes from January to September, so we utilize all data to compare male and female drivers. Figure 10 shows the CDF of daily operation time of male drivers and female drivers. Although only a small number of female drivers for ridesharing services, their average daily operation time is longer than

Table 1 Age related comparisons

Age groups	Daily operation time (h)				Daily operation distance (km)				Daily income (CNY)				Order entropy			
	EV		GV		EV		GV		EV		GV		EV		GV	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
20–24	4.09	2.35	3.6	2.35	84.17	48.51	79.7	51.08	320.61	179.7	319.74	223.18	4.6	1.2	4.38	1.23
25–29	4.16	2.38	3.71	2.38	87.42	50.29	84.15	55.55	333.1	184.94	346.59	238.37	4.48	1.39	4.4	1.28
30–34	4.27	2.5	3.7	2.43	90.39	52.34	84.2	57.19	345.63	195.85	354.4	254.74	4.48	1.39	4.4	1.29
35–39	4.25	2.49	3.64	2.47	90.16	52.06	81.3	58.01	344.94	192.27	345.86	261.28	4.5	1.35	4.4	1.2
40–44	4.43	2.56	3.77	2.49	92.35	53.13	81.06	56.56	355.63	196.52	345.8	255.7	4.56	1.33	4.49	1.2
45–49	4.62	2.53	4.02	2.5	94.25	51.23	84.73	56.21	362.5	188.3	362.92	254.88	4.6	1.25	4.57	1.13
50–54	4.76	2.55	4.05	2.46	95.62	50.85	82.76	53.59	368.51	189.01	353.59	243.91	4.6	1.26	4.6	1.0
55–59	4.85	2.59	4.13	2.42	95.8	51.51	82.49	51.52	367.96	195.39	345.39	227.89	4.75	1.24	4.67	0.96
60–64	4.05	2.54	3.62	1.92	86.03	54.31	73.28	42.3	326.59	206.67	290.12	167.72	4.46	0.57	4.80	0.80

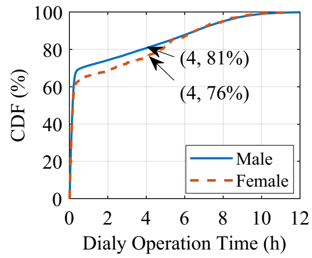


Fig. 10 Operation time of male and female drivers

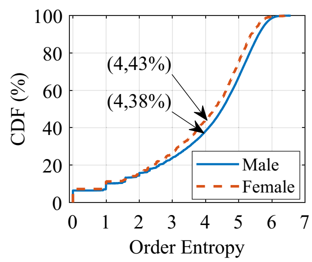


Fig. 11 Order entropy of male and female drivers

male drivers, e.g., 24% of female drivers operate longer than 4 h per day, but only 19% of male drivers operate longer than 4 h per day. There are similar patterns for daily operation distance and income, so we do not show them.

Figure 11 shows *Order Entropy* of male drivers and female drivers. We found male drivers operate in more regions than female drivers on average. For example, about 62% of male drivers operate in more than 16 regions on average, and about 57% of female drivers operate in more than 16 regions on average.

In summary, female drivers may operate a longer time in fewer regions than male drivers on average.

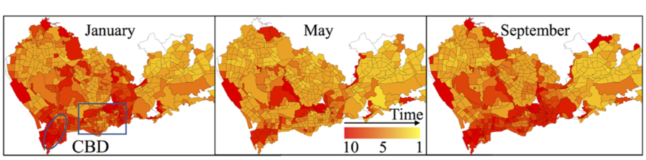
5 Impacts on passengers

In this section, we investigate the impact of the evolution of city-scale ridesharing with EV penetration on passengers' waiting time. The waiting time is defined as the time duration between a passenger sends a ride request through the App and the dispatched vehicle picks the passenger up.

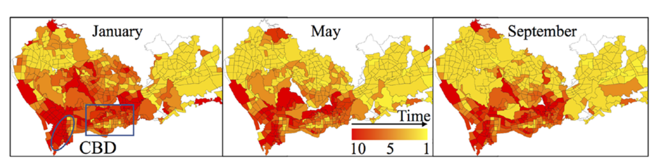
5.1 Qualitative measurement

We first investigate the average waiting time of passengers in different areas. Similarly, we utilize the urban partition with 491 regions to visualize the average waiting time of all orders in different months in each region, which is shown in Fig. 12a, where the lighter yellow parts mean shorter waiting time and the darker red parts mean longer waiting time in these regions. We found the light yellow part becomes larger from January to May, which means the waiting time in more areas becomes shorter. However, from May to September, the waiting time in many regions has increased. It should be noted that both the number of ridesharing vehicles (i.e., supply) and the number of orders (i.e., demand) increased from January to September.

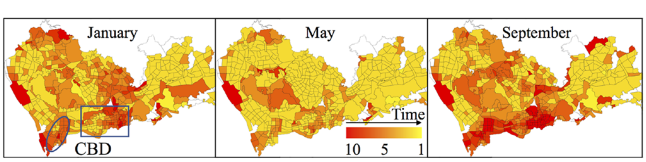
In addition, we also investigate the passengers' average waiting time evolution during rush hours and non-rush hours. As shown in Fig. 12b and c, for the morning rush hours, the average waiting time in most suburban (e.g., non-CDB) regions has significantly reduced from January to September, but the waiting time in urban areas does not reduce too much. One possible reason is that there are more EVs in the suburban areas during the evolution process, and they



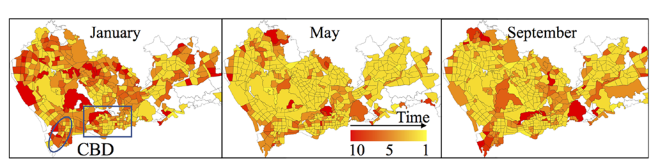
(a) Daily Average Waiting Time (mins)



(b) Average Waiting Time During 8:00-10:00 (Morning Rush Hour)



(c) Average Waiting Time During 17:00-19:00 (Evening Rush Hour)



(d) Average Waiting Time During 4:00-6:00 (non-Rush Hour)

Fig. 12 Visualization of passengers' average waiting time evolution in 491 regions provide more rides in suburban areas, as shown in Fig. 4, which potentially reduces the vehicles to serve passengers in urban areas.

Figure 12d shows the average waiting time during non-rush hours, and we found that from January to September, the average waiting time of passengers' has decreased in most regions, especially for the suburban areas. One potential reason would be more EVs increase and operate in suburban areas.

5.2 Quantitative measurement

We define the vehicle *accessibility* and *deficiency* to quantify the relation between passenger waiting time and the number of observed vehicles and orders, which are described as follow:

$$Accessibility(i) = \frac{\mathcal{N}_{driver}(i)}{\mathcal{N}_{order}(i)} \tag{5}$$

$$Deficiency(i) = \mathcal{N}_{order}(i) - \mathcal{N}_{veh}(i) \tag{6}$$

Where $Accessibility(i)$ is the vehicle accessibility in the *ith* hour in a day, denoting the average number of vehicles available to each order; $Deficiency(i)$ is the vehicle deficiency in the *ith* hour in a day; $\mathcal{N}_{veh}$ is the number of vehicles in the *ith* hour; $\mathcal{N}_{order}$ is the number of orders in the *ith* hour.

We first calculate the average waiting time of each hour, and then we obtain 24 values for each month. We show the waiting time and *accessibility* of each hour in Fig. 13, and we found with the increase of *accessibility*, the waiting time decreases. This phenomenon exists in all months. We also show the *deficiency* and waiting time in Fig. 14, where we found the waiting time increases with the increase of *deficiency*.

We further compare the correlation between the waiting time of passengers and some relevant factors, including the number of orders $\mathcal{N}_{order}$, *accessibility*, and *deficiency*. The Pearson correlation coefficient r and p-value are shown in Table 2. We found that from January to September, the correlation between passenger waiting time and $\mathcal{N}_{order}$ or

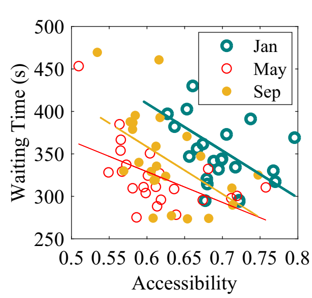


Fig. 13 Waiting time vs. accessibility

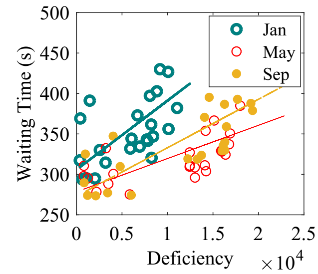


Fig. 14 Waiting time vs. deficiency

deficiency becomes larger, which means with more EV penetration, passengers are more vulnerable to longer waiting time if there are too many concurrent orders.

The relation between waiting time and *accessibility* is negative correlation, and the largest value happens in May, but the waiting time will be smaller with the increase of vehicle *accessibility* as shown in Fig. 13, which indicates it may need a significant large number of vehicles to reduce much waiting time of passengers with the penetration of large-scale EVs into the ridesharing services.

Even though we do not explicitly study the impacts of other factors (e.g., traffic conditions and weather conditions) on passengers' waiting time, they are implicitly included in our measurement since we consider the real-time demand and supply (i.e., passenger orders and available vehicles).

6 Impacts on society

In this section, we try to quantify the benefit of ridesharing EVs to our society during the evolutionary vehicle electrification process. Specifically, We utilize the CO_2 emission reduction as a metric to show the benefit of the penetration of EVs into the ridesharing services. We consider the real-world traffic conditions (e.g., travel speed), the daily operation distance, and daily operation time of EVs to more accurately estimate CO_2 emission reduction (Oguchi et al. 2002), which is shown as

$$E = C \times \left[0.3T + 0.028D + 0.056 \sum_{t=1}^{k} (\mathbb{1}_i * (v_t^2 - v_{t-1}^2)) \right] \tag{7}$$

where E is the CO_2 emissions (g); C is the coefficient between petrol consume and CO_2 emissions, which is 2392 g (CO_2)/liter of petrol for cars (ecscore 2019) in Shenzhen; T is the total operation time of vehicles (s); D is the total operation distance of vehicles (m); k is the total number of GPS records of each vehicle; v_t is the speed at time t (m/s); $\mathbb{1}_t$ is a tow-value indicator, which is 1 when $v_t > v_{t-1}$ (i.e., accelerating) otherwise it is 0.

Table 2 Correlation between waiting time and some factors

Waiting time	January		May		September	
	r	p	r	p	r	p
$\mathcal{N}_{order}$	0.567	0.0039	0.613	0.0015	0.761	< 0.0001
Deficiency	0.646	0.0006	0.693	0.0002	0.777	< 0.0001
Accessibility	−0.522	0.009	−0.551	0.0052	−0.527	0.008

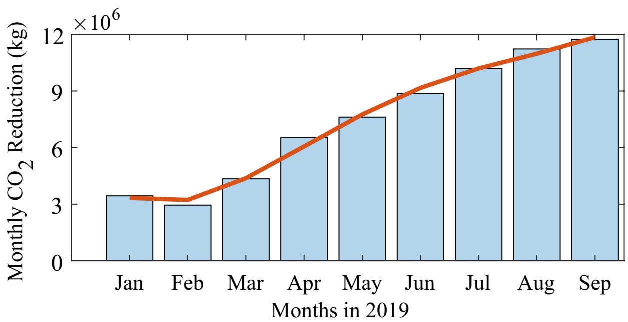


Fig. 15 Evolution of CO_2 reduction

We utilize the GPS records of all ridesharing EVs to estimate their CO_2 emission reduction. Figure 15 shows the monthly CO_2 emission reduction from January 2019 to September 2019, and we found that the CO_2 emission reduction has significantly increased from 3.44×10^6kg to 1.17×10^7kg during this period. There is a slight decrease in February as it includes the Chinese New Year (i.e., Spring Festival), so both the ridesharing supply and demand decreased, resulting in the CO_2 emission reduction in February lower than other months.

We depict the CO_2 emission reduction evolution due to the penetration of EVs into the ridesharing services by using a quartic function with the coefficient of determination $R^2 = 0.9942$, as shown below:

$$E(Y_M) = 8.913 \times 10^3 \cdot {Y_M}^4 - 2.10791 \times 10^5 \cdot {Y_M}^3 + 1.671877 \times 10^6 \cdot {Y_M}^2 - 3.781144 \times 10^6 \cdot Y_M + 5.642903 \times 10^6 \tag{8}$$

Where Y_M is the month of the year, and Y_M starts from Jan 2019, which means Jan 2019 is 1 in Eq. 8. If all the ridesharing GVs are replaced with EVs by the end of 2020, it is expected the yearly CO_2 reduction due to the ridesharing EVs will be over 5.9×10^8kg in Shenzhen in 2021, which is equivalent to the CO_2 emissions from 102,888 homes' electricity use for one year or CO_2 emissions from 2.92×10^8 kg of coal burned (Agency 2018). This finding indicates that EV penetration into ridesharing services may have a huge potential to reduce CO_2 emissions and make a more sustainable society.

7 Discussion

In this section, we summarize our findings and discuss some implications and limitations of our work.

7.1 Findings and insights

We summarize some findings and insights obtained from our longitudinal study in Table 3.

7.2 Implications

We believe that our efforts and the revealed insights in Table 3 can contribute to different roles in our society for policy suggestions, e.g., (i) ridesharing drivers, (ii) operators and governments, and (iii) related researchers.

For ridesharing drivers Our findings have the potential to encourage ridesharing drivers to replace their GVs with EVs since most EV drivers' income did not decrease when they work long daily time to provide ridesharing services. Since most ridesharing usages are short trips, e.g., 75% of trips are within 10 km, drivers do not need to worry that they cannot provide services for most trips. Some locations can be recommended for EV drivers to operate, e.g., some CBD areas, as there is high demand while inadequate supply.

For ridesharing operators and city governments It would benefit our society to replace ridesharing GVs with EVs since EVs have the potential to achieve huge greenhouse gas emission reduction, which could pave the way for more sustainable mobility. However, it may be not the best decision to replace 100% of GVs with EVs under the current setting (e.g., low battery capacity and the long charging time of EVs) since some long inter-cities trips may not be fulfilled by EVs. Ridesharing operators and city governments can replace 90% of their ridesharing GVs with EVs at the first stage of vehicle electrification. In addition, with high EV penetration, more EVs are needed to reduce passengers' waiting time. The government should deploy more charging infrastructures in CBD areas to encourage more EV drivers to operate there, which is also necessary for large-scale EV penetration into ridesharing services. With the development

Table 3 Findings and insights

Findings obtained from our longitudinal study	*S*patial and *T*emporal Evolution	*(ST1) distance* We found there are more EV drivers operating in suburban (e.g., non-CBD) areas. Almost all regions of high *spatial ratios* of EVs (i.e., percentage of orders served by EV drivers in a region) are in the suburban areas, as shown in Fig. 4. The *spatial ratios* of EVs in 93.7% of regions are not larger than 0.3 in January, but the *spatial ratios* of EVs in 92.7% of regions become over 0.5 in September, which means the ridesharing service in Shenzhen has converted from a GV-dominating market into an EV-leading one during the rapid EV penetration process. *(ST2) Potential of EVs for Ridesharing* EV drivers typically operate in more regions than GV drivers based on our observations, which may imply the range limitation of EVs may not hinder their daily operation in most cases and EVs have the potential to replace GVs for ridesharing services, as shown in Fig. 5. *(ST3) Temporal Evolution* The served order distributions of EVs and GVs are similar during the evolution process, which potentially indicates that operators dispatch the vehicles to serve passengers without considering they are EVs or GVs, so passengers cannot decide the serving vehicle types (i.e., EVs or GVs)
	*I*mpacts on *D*rivers	*(ID1) Income* EV drivers typically have higher daily income than GV drivers due to the longer daily operation distance and time. However, almost all long trips (e.g., cross-city trips) with very high costs are served by GV drivers due to the battery capacity and long charging time of EVs, which indicates that EVs cannot fully replace the GVs for long trips under the current setting (Fig. 7).*(ID2) Age* ① The newly registered ridesharing drivers are more likely to be young EV drivers, e.g., the ratio of young EV drivers with age under 40 has increased from 61.7% to 68.2% from January to September 2019 (Fig. 8), while the counterpart of GV drivers has not increased much during this period (Fig. 9). ② Middle-aged drivers (e.g., 45–59) have the longest average daily operation time, distance, and income compared to drivers of other ages (Table 1). *(ID3) Gender* Only 1.1% of ridesharing drivers are female. Although the average daily operation time of female drivers is longer than that of male drivers (Fig. 10), the number of operation regions of them is less than male drivers on average (Fig. 11)
	*I*mpacts on *P*assengers	*(IP) Waiting Time* With more EVs penetrating into the ridesharing services, passengers are more vulnerable to longer waiting time if there are too many concurrent orders. We found passengers' waiting time has a strong correlation with the deficiency of ridesharing vehicles, with Pearson $r = 0.777$ and $p < 0.0001$ in September 2019 (Table 2)
	Impacts on society	*(IS) CO_2 emissions* EVs have a huge potential to reduce the CO_2 emissions for ridesharing services, e.g., we found the ridesharing EVs in Shenzhen reduced 1.17×10^7kg CO_2 emissions in September 2019 (Fig. 15), which is equivalent to the CO_2 emissions from about 24,500 homes' electricity use for one month or CO_2 emissions from 5.8×10^6kg of coal burned

of battery technology and charging technology, we believe the GVs may be fully replaced by EVs.

For researchers With more and more cities advocating vehicle electrification, the ever-increasing number of EVs for ridesharing services must have huge impacts on our society, and the EV topic also attracts a lot of interest in the research community (Du et al. 2018; Li et al. 2015; Wang et al. 2019b; Xiong et al. 2015). In this paper, we provided a first look at the EV penetration into ridesharing services, and we found ridesharing EVs have many different patterns from conventional GVs. However, there are still many veiled questions, e.g., the impact of ridesharing EVs on smart grids, individual drivers' operation pattern change, the impact of EVs on individual drivers, etc. Although our work can lay the foundation for some of these works, having access to the ridesharing EV data is still a problem for most researchers. Hence, to benefit the research community and make our work more reproductive, our collaborator agrees to release sample data used in this paper after we can reveal our identity.

7.3 Ethics and privacy

As the utilized data is from real ridesharing services, we took careful steps to ensure that our work met ethical standards. (i) The staff in the Transport Commission of Shenzhen removed all sensitive information about drivers and passengers, and they replaced all driver IDs with unique identifiers, so all of the identifiers in our datasets are opaque IDs. (ii) We only collected GPS coordinates of ridesharing vehicles when they were on duty, which means we did not collect their information when these vehicles were used for personal purposes, so we did not obtain the personal private trajectory information of drivers. (iii) All users and drivers have been notified their order data or vehicle information will be collected for ridesharing management and payment evaluation when they register to use or provide ridesharing services. Users and drivers consented that their data while using/providing ridesharing services can be utilized to understand and improve the services of the ridesharing operators by signing a contract when registering.

7.4 Limitations and future work

Cross-city investigation In this work, we only utilize ridesharing data from the Chinese city Shenzhen to investigate the penetration evolution of EVs for ridesharing services. Due to certain features of Shenzhen (e.g., one of the most crowded cities in China with the fastest economic growth, a pilot city to replace ridesharing GVs with EVs), the results we have in Shenzhen may not be directly applied to all other cities. *Although there are no signs that the same results will hold to a different city*, we argue that our longitudinal study and obtained insights can provide guidelines for other cities (e.g., London) to understand and predict their ridesharing evolution when replacing GVs with EVs.

We are also trying to conduct a dual-city investigation. However, since only Shenzhen has such a large-scale and high penetration of EVs for ridesharing services currently, it is challenging to find another city for a parallel study. One possible direction we are exploring is to design transfer learning models to transfer the knowledge (e.g., spatiotemporal patterns of EVs, increasing rate of EVs) we obtained from the Shenzhen ridesharing services to other cities for a "what if" investigation. For example, what if all ridesharing GVs in London or New York City were replaced by EVs, how it will influence different parties within the ridesharing service. It also opens some very interesting research directions.

Including charging data of EVs In this project, we have no access to the real-world charging data of ridesharing EVs, so we did not have opportunities to study their charging patterns. Based on our field studies in Shenzhen, we found the charging activities of ridesharing EVs are extremely complicated due to their private vehicle nature. Different from other commercial EVs, e.g., electric buses, which usually charge in their exclusive charging stations, ridesharing drivers may charge their EVs at any place with charging points at any time, so their charging behaviors are more complicated. One possible direction we are exploring is to infer the charging activities of ridesharing EVs based on their GPS data.

8 Related work

As ridesharing services continue to gain popularity of the research community, there is an emerging body of research on them (Anwar et al. 2017; Zhou et al. 2019; Kooti et al. 2017; Guo et al. 2017a; Bokányi and Hannák 2019; Shokoohyar 2018; Lan et al. 2019; Bansal et al. 2019; Wang et al. 2018a; Li et al. 2019; Xu et al. 2018; Lin et al. 2018). In general, most existing works on ridesharing services can be classified into the following two categories: (i) understanding ridesharing services based on real-world data; and (ii) enhancing ridesharing services by designing some optimization algorithms (Li et al. 2019; Wang et al. 2018a).

8.1 Understanding ridesharing services

There is a set of research conducted on understanding different dimensions in ridesharing services (Jiang et al. 2018; Kooti et al. 2017; Guo et al. 2017a; Bokányi and Hannák 2019; Shokoohyar 2018; Lan et al. 2019; Bansal et al. 2019). Jiang et al. (2018) took a comprehensive look at the competition and accessibility of Uber, Lyft, and taxis in two major U.S. cities. Kooti et al. (2017) conducted a study to reveal the demographic and socioeconomic factors that affect participation in the ridesharing market. Guo et al. (2017b) conducted research to understand the demand and dynamic pricing in ridesharing services, and they also investigated the patterns of passengers' reactions to dynamic prices Guo et al. (2017a). Bokányi and Hannák (2019) combined approaches from complex systems and algorithmic fairness to investigate the effect of algorithm design decisions on wage inequality in ridesharing services. Lan et al. (2019) systematically studied the impact factors and their relations to ridesharing services in an empirical way. Bansal et al. (2019) provide some new insights on understanding preferences to use ridesharing services by identifying relationships of individuals' socio-demographic characteristics with their preferences to use ridesharing services. However, these works rarely consider the evolution of ridesharing services, which potentially causes incomplete observations, especially for the characteristics of ridesharing EVs.

8.2 Improving ridesharing services

There is also an increasing number of existing work focusing on improving ridesharing services, e.g., increasing drivers' incomes (Chaudhari et al. 2018), and reducing passengers' waiting time (Zhang et al. 2017), balancing demand and supply (Wang et al. 2018a; Tang et al. 2019; Li et al. 2019; Xu et al. 2018; Lin et al. 2018). Chaudhari et al. (2018) focused on the problem of maximizing a driver's individual earnings on ridesharing platforms like Uber or Lyft, and they described a series of dynamic programming algorithms to solve this problem. Fang et al. (2018) aimed to target the optimal loyalty program (subsidy) design. The results show that heterogeneity in users helps reduce the competition among platforms, and they validated the results with real transaction data from a ridesharing platform. Much of the recent literature focuses on the ridesharing order dispatching. Xu et al. (2018) presented a novel order dispatch algorithm to provide a more efficient way to optimize resource utilization and user experience in a global and more far-sighted view. Wang et al. (2018a) modeled the ridesharing order dispatching problem as a Markov Decision Process and proposed learning solutions based on deep Q-networks with an action search to optimize the dispatching policy for drivers on ridesharing platforms. Li et al. (2019) tried to address the ridesharing order dispatching problem using multi-agent reinforcement learning, which shows the ability to capture the stochastic demand-supply dynamics in large-scale ridesharing scenarios. However, these works did not consider the penetration of EVs into the ridesharing services, without considering characteristics of EVs potentially making their solutions do not work on EVs.

8.3 Uniqueness of our work

Our paper is in the first category, i.e., understanding ridesharing, but it has unique features compared to existing works. Our work investigates the evolution of city-scale ridesharing when it encounters the vehicle electrification (Wang et al. 2018b, 2020a, c, 2021b, 2022a, b), which, to our knowledge, has not been studied by existing research, which has the potential to lay the foundation for improving ridesharing and other following research.

9 Conclusion

In this paper, we conduct the first longitudinal study to understand the evolution of ridesharing services with large-scale EV penetration. Specifically, our analysis covers over 165 million ridesharing orders collected from all ridesharing operators in the Chinese city Shenzhen over a period of 9 months, during which the number of EVs for ridesharing services has significantly increased from 8k to 24k. Different roles in ridesharing services (e.g., passengers, EV and GV drivers, and operators) are investigated. We provide a set of insights regarding the evolution of city-scale ridesharing services with large-scale EV penetration, e.g., differences in spatial & temporal patterns and incomes of EV and GV drivers, passengers' waiting time, etc. The evolution of drivers of different demographic characteristics is also investigated. In addition, we also quantify the benefits of ridesharing EVs for the CO_2 emission reduction. We believe that our research efforts and obtained insights (e.g., EV drivers have the potential to achieve higher daily profit than GV drivers) have the potential to benefit ridesharing drivers and operators, and also attract the focus of the research community. The uncovered advantages and drawbacks of ridesharing EVs may also provide guidelines for other cities when replacing their GVs with EVs.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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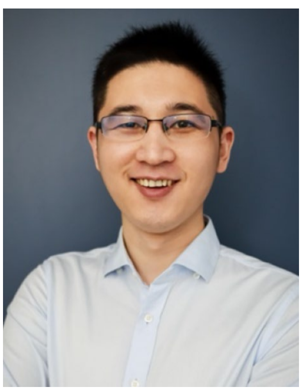

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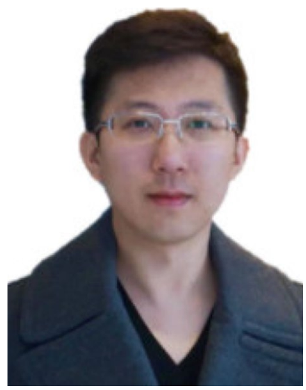

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