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Understanding Ridesourcing Mobility and the Future of Electrification: A Comparative Study in Beijing

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ABSTRACT

The development of mobile Internet, smartphones, and location-based services has enabled ridesourcing, which pools vehicles and drivers to provide on-demand travel services. As an alternative transportation option, ridesourcing has significant impacts on urban travel. However, the unique mobility pattern of ridesourcing and its impact on vehicle electrification have not been well studied. To address this gap, this paper presents a comparative, big-data-driven framework to characterize the ridesourcing mobility pattern, and evaluate the acceptance potential of electric vehicles for ridesourcing in comparison with other types of vehicle use. Multi-temporal resolution ridesourcing trips are extracted from raw GPS trajectories. The patterns of three urban travel (household, ridesourcing, and taxis) are extracted from GPS trajectories in Beijing, and compared. The electrification potentials of these types of travel under different charging levels are then evaluated. The results demonstrate that mobility patterns of household, ridesourcing, and taxi drivers are similar when a single trip is considered but differ significantly when total vehicle travel is considered. We show that potential acceptance of electric vehicles decreases significantly from household to ridesourcing and taxi vehicle use. These findings provide useful insights into of the role vehicle electrification can play in sustainability of urban personal transportation across a range of drivers.

KEYWORDS

Urban mobility; electric vehicle; electrification; ridesourcing; GPS trajectories

Introduction

Transportation consumes 28 percent of global energy and produces 23 percent of global greenhouse emissions (IEA, 2018). Providing sustainable transportation is a major challenge and opportunity to reduce energy and environmental issues. With the development of 4G/5G communication, mobile Internet, smartphones, and artificial intelligence, transportation is experiencing disruptive innovations. The combination of ridesourcing, connected vehicles, electric vehicles (EVs), and autonomous vehicles, will change the urban mobility landscape (Santi et al., 2014; Ronald et al., 2017; Duarte and Ratti, 2018; Sperling, 2018). In addition to innovation in vehicle technologies, ridesourcing refers to an alternative transportation option which pools vehicles and drivers to provide a ubiquitous on-demand travel service (Barann et al., 2017). Recently, there are many terms used to describe this emerging transport option, such as ride-sharing, ride-hailing, ride-splitting,

CONTACT Wei Tu tuwei@szu.edu.cn
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and transportation network companies (Shaheen and Cohen, 2019). Here, we used the term ridesourcing to describe the transportation option connecting voluntary drivers with passengers via mobile devices and applications (Jin et al., 2018). Ridesourcing companies have been expanding rapidly across the world (e.g., Uber and Lyft in the United States, Didi Chuxing and Shenzhou Zhuanche in China, Ola in India, Go-Jek in Indonesia, and Grab in Singapore).

Ridesourcing integrates innovative information and communication technologies and smart, demand-responsive operations to provide flexible and user-friendly mobility services. Different from drivers of private cars and taxi drivers, ridesourcing drivers voluntarily cruise on the road, accept travel requests via mobile devices, and deliver clients to their destinations. Ridesourcing drivers can enter into and exit the dynamic market according to their personal schedules. Because of features such as convenience, low-cost, and dynamic pricing to attract both drivers and customers, ridesourcing has gained a significant market share in urban transportation. Accordingly, ridesourcing travel plays a significant role in the urban mobility landscape. Previous studies have revealed several impacts, such as competing with taxis (Nie, 2017; Su et al., 2018), improving the accessibility of low-income people (McArdle, 2015), increasing the vehicle occupancy rate (Santi et al., 2014), and reducing greenhouse emission (Yu et al., 2017). However, the mobility pattern of ridesourcing has not been well studied, especially considering the diversity of ridesourcing drivers. There are several open questions: (1) does ridesourcing travel hold a pattern? (2) are the mobility patterns of ridesourcing travel similar to that of household and taxi travel? The present work builds upon our recent study of the cost, acceptability, and energy consumption of electric vehicles for ride hailing drivers in Beijing (Tu et al., 2019), including an investigation of the relationship between different EV penetration rates and trip length. Compared with Tu et al. (2019), this study adds a comparative analysis of household, ride hailing, and taxi drivers, and focuses on the needs for charging infrastructure to support the electrification of the fleet.

EVs introduce another innovation to urban mobility as the widespread use of this technology would significantly alleviate energy consumption and reduce carbon emissions (Tu et al., 2019). However, EV still struggle to find wide acceptance in the market: although the yearly EV sales exceeded the 1-million milestone in 2017 (IEA, 2018), they still represent less than 2 percent of global vehicle sales. The diffusion of EVs is hampered by their short driving range, long charging time, and the sparsity of charging stations. The extent to which EVs can be accepted depends on customer demographic and socioeconomic status (i.e., age, gender, income, education, car-ownership, etc.) (Liao et al., 2018), EV characteristics (driving range, charging rates) (Yang et al., 2018), charging infrastructure access (Tu et al., 2016), and mobility patterns (travel distance, parking duration) (He et al., 2016; Tu et al., 2019). The ability of EV driving range to meet daily travel distance is an obvious critical factor in enabling EV adoption. Analyzing mobility patterns of ridesourcing is then essential to estimate its ultimate electrification potential, and requires considering the spatial-temporal features of ridesourcing travel. Comparing these patterns with those of household and taxi travel, it is possible to derive useful insights guiding the use of EVs for different vehicle uses.

To summarize, this article presents a data-driven comparative study to reveal ridesourcing mobility patterns and evaluate their electrification potential in the future. Multi-temporal resolution ridesourcing travel trips are extracted from raw GPS trajectories using

machine learning. Mobility patterns of three typical urban travels including household travel, ridesourcing, and taxis travel are modeled and compared. Their electrifications are evaluated by considering travel distance, traveling-parking cycles, and EV driving range. The case study was implemented in Beijing with GPS trajectories of 459 private cars, 144,867 ridesourcing vehicles, and 44,454 taxis. The results demonstrate that (1) household, ridesourcing, and taxi travel are similar when an individual travels, but different when daily vehicle travel is considered; (2) the general electrification potential decreases from household to ridesourcing and taxis; (3) the spatial distribution of parking demand for ridesourcing vehicles and taxis is different. These findings provide useful insights into understanding the unique features of ridesourcing mobility and can benefit policy-making for promoting EVs in ridesourcing communities in the future.

The article is organized as follows: the next section offers a review of the literature related to urban mobility, ridesourcing, and electric vehicles. Then we describe the datasets used in this study. After that, we present the GPS trajectory-driven approach to discover mobility patterns and assess the potential of electrification. We then analyze the experiment results before offering a conclusion to the study and an outline of future work.

Literature Review

Patterns of Human Mobility

Understanding human mobility is necessary for transportation planning and management (Bengtsson et al., 2015; Ren et al., 2014). Travel distance is the most critical indicator of human mobility. Several empirical studies show that aggregated human travel follows the power law in which the probability of making a trip of a certain distance d decays with d following the power function (Brockmann et al., 2006). A few studies also observe the exponential law behind massive daily travels, in which travel count decreases with travel distance, following the exponential function (Song et al., 2010; Liang et al., 2012). The difference is largely due to different data sources or different travel groups (Zhao et al., 2015). For example, Yan et al. (2013) reported that the aggregated power law of human mobility cannot be observed at the individual level. They also found that individuals with different occupations have different mobility patterns.

Empirical studies also analyzed motorized travels. For example, Jiang et al. (2009) studied GPS trajectories of 50 taxis in four Swedish cities for six months and found that taxi passengers' travel distance obeys the power-law. Liang et al. (2012) argued the distributions of the taxi trip displacement follows the exponential distribution rather than the power law. Similar results have been demonstrated in Shanghai (Peng et al., 2012). Since the taxi GPS records are mixed with travels of many passengers, patterns of household travels should be derived from private cars' trajectories, rather than taxi trajectories. Bazzani et al. (2010) studied the travel patterns using trajectories of private cars in Italian cities, and their results show that travel distance consistently follows the exponential distribution across different cities and time periods.

Ridesourcing is a relatively new type of urban mobility, and only a few studies attempted to characterize its use. Dong et al. (2018) unraveled the spatial distribution and temporal dynamic of ridesourcing travels in Beijing. However, they failed to reveal the scaling laws in their works. These findings suggest that there might be differences

between the features of household, ridesourcing, and taxi travels, and highlight the need for a comparative study.

Impact of Ridesourcing

Ridesourcing pools vehicles and drivers to provide on-demand travel services. As an alternative travel mode, ridesourcing has great effect on urban transport. Generally, many people share one vehicle in ridesourcing (Vazifeh et al., 2018); therefore, it will increase the Vehicle Miles Traveled (VMT) in the metropolitan area, such as Seattle, San Francisco, and Boston. On the other hand, ridesourcing companies sense road traffic and intelligently dispatch vehicles in cities to match real-time travel demands. Using data scraped from the application programming interfaces of Uber and Lyft, combined with observed travel time data, Erhardt et al. (2019) demonstrated that ridesourcing increases rather than reduces congestion.

Because of its efficiency and economy, ridesourcing is eroding travel by household vehicles and public transit (Henao, 2016). Many studies further revealed that ridesourcing competed with public transit for some individual trips (Rayle et al., 2016), but it might sometimes serve as a complement. Ridesourcing fills in the spatial and temporal gaps in public transit networks, therefore improving transportation accessibility (Silva et al., 2018). From the spatial perspective, ridesourcing might serve as a feeder for public transit, alleviating the first-mile/last-mile problem. For example, Jin et al. (2019) observed that Uber trips are higher in Queens, New York, where public transit coverage is lower. But Uber travel is still very high in Manhattan, the highest density area in the world with extremely high public transit coverage. From the temporal perspective, ridesourcing is frequently used during the evening (8PM–10PM) and late-night and early morning hours (11PM–4AM) when the public transit supply is insufficient (Dong et al., 2018; Tu et al., 2018).

Ridesourcing also has great influence on the taxi industry. Su et al. (2018) reported that by taking e-hailing Apps for taxis, more taxis trips occurred. Meanwhile, ridesourcing was found to compete with taxis in hours and in the central business area. Using five-year taxi GPS trajectories, Nie (2017) explored where, when, and how ridesourcing affects taxis. He reported that the taxi industry in Shenzhen experienced a significant loss in its ridership, but the shock of ridesourcing was relatively short and the losses of the taxi industry stabilized quickly. Cramer and Krueger (2016) measured and compared the capacity utilization of both UberX and taxi in several US cities, including New York City, San Francisco, Seattle, and Los Angeles. They revealed that UberX's capacity utilization rate is much higher than that of taxi drivers, because of e-hailing, Uber's flexible pricing, and inefficient taxi regulations. These studies demonstrate the significant influences of ridesourcing on urban travels; therefore, they highlight the necessity of a comparative study of alternative modes of urban passenger car travel.

Acceptance of Electric Vehicles

The acceptance of EVs is very important for a transition to future green transportation. Traditional approaches to revealing preferences related to EVs rely on surveys. They found that the customer's attitude to EVs was affected by age, gender, income, education,

car-ownership, and psychological factors (Zhang et al., 2011; Liao et al., 2017). In terms of taxi drivers, Wang et al. (2018) conducted a survey in Hong Kong and found that the EV subsidy, rental income, and battery lifespan were influential to the owners, while fare income, the rental cost, the access time to chargers, and the range per charge significantly affected taxi drivers' decisions regarding shifting to EVs.

The ability of EV driving range to meet travel distance is critical for enabling EV adoption. The extent to which EVs can be accepted by customers is largely determined by mobility patterns (trip length and parking duration), EV characteristics (driving range and charging rates), access to charging infrastructure, and economics (Tamor et al., 2013). Potential EV adoption can be assessed from an analysis of travel patterns (Cai, 2015; Cai et al., 2016; He et al., 2016; Tu et al., 2018; Tu et al., 2019). Using the 2009 national household travel survey (NHTS) dataset, Needell et al. (2016) found that relying only on night-time charging, the 2013 Nissan Leaf with a 19.2 kWh battery could meet the energy requirement of 87 percent of vehicle-days in the United States. Kelly et al. (2012) describe a compact vehicle with a 10.4 kWh useable battery that travels between 62.5 and 75.7 percent on battery electricity, depending on charging scenarios. Gennaro et al. (2013) characterized vehicles' driving patterns using 160,000 vehicles in the province of Modena, Italy, and evaluated the electrification potential. These studies provide useful insights in characterizing the electrification future. Following this approach, and motivated by the above discussion about the difference in mobility patterns of personal transportation, in this paper we examine EV acceptance of ridesourcing and compare it with household and taxi travels to inform EV policy-making.

Datasets

The study was conducted in Beijing, China, a mega-city with a population of 22 million and 5.64 million vehicles. Three vehicle GPS datasets were processed to reveal the mobility patterns of household, ridesourcing, and taxi drivers, and to evaluate their electrification potential. Table 1 reports the details of these datasets. Note that to protect privacy personal information about drivers and clients was not included in the dataset.

Household GPS Trajectory Dataset

This GPS dataset was contributed to by 459 volunteers with conventional private cars. Their GPS trajectories were collected for automobile carbon emission evaluation during the period 2013–2015, totally covering 3.3 million km. All trajectories cover at least

Table 1. Statistics for three datasets in Beijing considered in the present study

Dataset	Number of vehicles	Period covered	Data cleaning operations
Household	459	1–7 months	Deleted trajectories with travel distances less than 10 m, average trip speeds lower than 3.2 km/h, and unreasonable trajectories with off-the-chart locations.
Ridesourcing	144,867	1 week	Deleted short trajectories (< 3 minutes) and trajectories with abnormal speed (>40 meters/seconds)
Taxi	44,454	1 week	Deleted short trajectories (< 3 minutes) and trajectories with abnormal speed (>40 meters/seconds)

four weeks thus their daily driving and parking can be inferred. Although the sample size is not as big as ridesourcing and taxis, the volunteers were well selected to collect representative trajectories. Further details are available elsewhere (He et al., 2016).

Ridesourcing GPS Trajectory Dataset

Ridesourcing GPS trajectories were provided by the main ridesourcing player in Beijing. GPS points were recorded by smartphones of ridesourcing drivers after logging in. This dataset covers one week in 2015. On average, 70 gigabytes (GB) GPS points of 183,457 ride-hailing drivers were collected per day. After data cleaning, for example, deleting short trajectories (< 3 minutes) and trajectories with abnormal speed (>40 meters/second), trajectories of 144,867 ridesourcing drivers covering 104 million km were retained. Further details are available elsewhere (Tu et al., 2019).

Taxi GPS Trajectory Dataset

The taxi GPS trajectories were collected by the Beijing Transportation Information Center for real-time traffic monitoring. They span the same period of the ridesourcing GPS dataset. After data cleaning, GPS trajectories of 44,454 taxis covering 63.8 million km are left for further data mining.

Methodology

We present a data-driven comparative approach to reveal and compare three types of mobility patterns and their electrification potential. Using raw GPS datasets, alternative traveling and parking actions of ridesourcing and taxi drivers are detected using machine learning. The trips of household travelers are naturally segmented by reported parking. Mobility patterns of household, ridesourcing, and taxi drivers are revealed by modeling the distribution of travel distance. Finally, considering the EV driving range and different options for charging infrastructure, the electrification potential of three types of urban travels are evaluated and compared. The workflow used to perform the study is reported in Figure 1. The

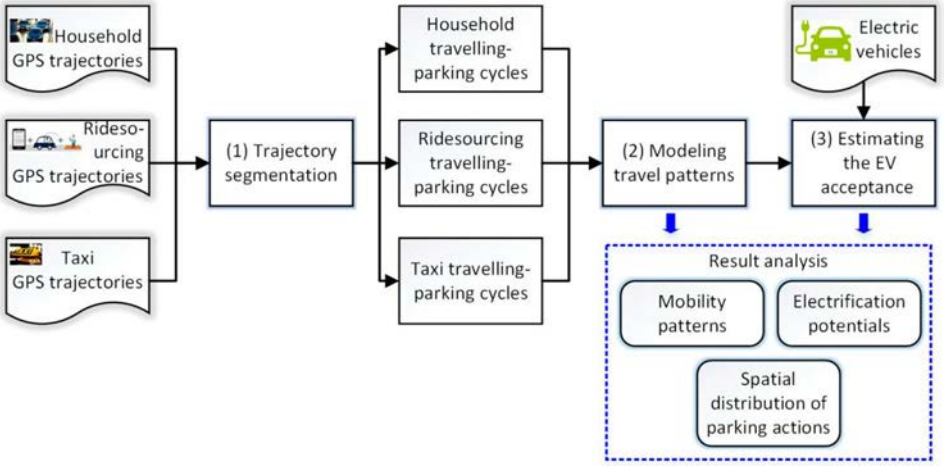

Figure 1. Workflow used to evaluate mobility patterns and electrification potentials

approaches used are inspired by our previous studies (Tamor et al., 2013; He et al., 2016; Tu et al., 2019) and updated to keep the analysis consistent and relevant across three urban travel datasets. More details are given in the following sections.

Trajectory Segmentation

Raw GPS points record the time and the position of vehicles. But traveling and parking are not explicitly labeled. Due to the positioning error, although the vehicle stops at some places when picking up, or dropping off a traveler, the reported GPS points still vary within a circle of radius 20 to 100 meters, depending on the urban environment and GPS receivers in drivers' smartphones. Consequently, travel actions cannot be recognized by simply looking at the raw GPS coordinates.

We used machine learning to infer traveling and parking actions. First, raw GPS points were segmented into tentative travel segments and parking segments. To identify parking actions, we filtered GPS points with a travel speed below a pre-defined threshold α. In this study, we defined the threshold α to 1 m/s to distinguish a moving point or a possible parking point. Then, we recognized the true parking from the set of potential parking points. A sequence of possible parking points forms a cluster, which may represent a true parking action. A set of features listed below are extracted for model training and implementation:

- *Time*, the duration (t_1) of action as reported in the group points, and their average sample interval (t_2)
- *Distance*, including the total recorded travel distance (d_1), the displacement (d_2), and the ratio of travel distance and displacement ($r = d_1/d_2$)
- *Speed*, containing the average speed (v), the maximum travel speed (v_{max}), the minimum travel speed (v_{min}), and the standard deviation of travel speed (v_{sd}).

After evaluating the performance of several machine learning methods, the support-vector-machine (SVM) was used to classify true parking points and false points. The SVM is a supervised learning model for classification, regression, and other learning tasks. SVM has been successfully applied in computer vision, natural language processing, remote sensing image processing, trajectory segmentation, etc. Basically, SVM constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space for the classification task. A good classification is achieved by the hyperplane with the largest distance to the nearest training data. In this study, GPS points of 1,000 ridesourcing drivers were manually labeled with "traveling" (1) and "parking" (–1) to train the SVM model, with the SVM package in *Scikit-Learn* (http://scikit-learn.org/). The SVM achieved the accuracy 0.85. Finally, the trained SVM model was used to label remaining GPS points with "traveling" or "parking."

According to real-world driving experience, we segmented raw GPS trajectories to extract trips and parking actions by setting the minimum parking duration to 1 minute. Finally, we extracted travel profiles from the corresponding GPS trajectory datasets.

Modelling Travel Patterns

Previous studies have demonstrated that daily-level and trip-level human travel follows the normal, lognormal (Plötz et al., 2017; Alessandretti et al., 2017), power-law (Zhao

et al., 2012), exponential (Liang et al., 2012; Cai et al., 2016; Zhao et al., 2017; Zhang et al., 2018), or exponential-truncated power law distribution (Gonzalez et al., 2008). Formally, the normal distribution and the lognormal distribution are presented by Eqs. (1) and (2) respectively:

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{1}$$

$$P(x) = \frac{1}{x\sigma_1\sqrt{2\pi}} e^{-\frac{(\ln x-\mu)^2}{2\sigma_1^2}} \tag{2}$$

Where x denotes travel distance, $P(x)$ denotes the probability of travel with distance x, μ denotes the mean, σ represents the standard deviation of the variable, and σ_1 represents the standard deviation of the natural logarithm of the variable.

The power-law distribution with an exponent α is defined as Eq. (3):

$$P(x) = ax^{-\alpha} \tag{3}$$

The exponential distribution is defined as Eq. (4), where λ is the rate parameter

$$P(x) = ae^{-\lambda x} \tag{4}$$

The truncated power law distribution is expressed as Eq. (5), where x_0 is the cut-off distance.

$$P(x) = (x + x_0)^{-\beta} e^{-\lambda x} \tag{5}$$

We employed the Akaike information criterion (AIC) method to compare candidate models as the AIC considers both the fitting with the actual data and the complexity of the models. The maximum likelihood estimate (MLE) method is adapted to fit the parameters. The AIC score for each candidate model i is calculated by Eq. (6), where L_i is the likelihood for the model i, which depends on the parameter value estimated by the MLE. K_i denotes the number of parameters in the model.

$$AIC_i = -2LogL_i + 2K_i \tag{6}$$

The relative likelihoods of the models are indicated by the Akaike weights w_i as Eq. (7), $\Delta_i = AIC_i - min(AIC_i)$, N is the number of candidate models. The model with the largest Akaike weight is most likely to be selected.

$$w_i = \frac{e^{-\Delta_i/2}}{\sum_{j=1}^{N} e^{-\Delta_i/2}} \tag{7}$$

Estimating the Acceptability of Electric Vehicles

While there are other factors that influence EV acceptance, the ability of EV driving range to meet travel distance is critical for enabling EV adoption. Here we refer to this metric and define EV acceptance based on their capability to fulfill travel demands, which

depends on the EV's driving range, travel patterns, and charging infrastructures. We assume that drivers will only substitute their vehicles with EVs if the BEV supports their travel needs without changing their current travel-parking cycles (Tu et al., 2019). In other words, the drivers will have sufficient opportunities to charge their vehicles to meet their driving needs. Following the principle of previous studies (Tamor et al., 2013; He et al., 2016), we estimated the EV acceptance $A(d)$ by comparing travel distance x and EV driving range d, as Eq. (8).

$$A(d) = P(x \leq d) = \int_0^d P(x)dx \tag{8}$$

Here, the EV acceptability denotes the upper electrification bound of household vehicles, ridesourcing vehicles, or taxis, as it assumes that (1) the charger is always available at parking places and drivers will always plug-in once parking, and (2) drivers have no risk aversion to adopting EVs, and (iii) drivers have no range anxiety.

As charging an EV for an excessively short time might not be practical, we merged short-term parking into successive long-time travel, thus forming trips separated by relatively longer parking times that can be used to charge EVs. For example, two consecutive trips with a one-minute stop will be merged into one long trip. Following the approach of Tamor et al. (2013) and He et al. (2016), three temporal-resolutions for aggregating travels where considered: *short-term parking*, where parking between consecutive (aggregate) trips must be at least 0.5 hours; *medium-term parking*, where the limit is set to four hours, mimicking a situation in which the EV is charged at workplaces; and *long-term parking*, where the limit is set to eight hours, corresponding to a charging at home. Note that many taxis may be parked for less than four hours in a day, and there would be no home parking for them. But we still kept the longest parking less than four hours. In other words, at least one parking would be reserved for one driver in a day. Finally, after the trip merging, we get trips associated with three types of parking respectively.

Drivers' parking implies the potential need for charging infrastructure. To understand the future charging infrastructure demand, we mapped the parking actions of ridesourcing and taxi drivers, respectively. Spatial patterns of charging infrastructures for ridesourcing and taxi drivers are further analyzed and compared.

Results

This section reports the mobility patterns of three types of urban travel, compares their electrification ranges, and discusses the implication for electrifying personal urban mobility.

Patterns of Urban Mobility

After processing raw GPS datasets, traveling and parking actions of ridesourcing drivers and taxi drivers were recognized. The descriptive statistics of three types of urban travel are reported in Table 2. They show that household drivers travel 46.4 km in 1.8 hours

per day, with three stops. The average trip distance is 13.7 km while the mean parking duration is 7.9 hours. In terms of ridesourcing travel, vehicle usage is heavier as daily travel is a mix of multiple personal travel. Ridesourcing drivers travel 129.4 km in 5.7 hours in a day, with nine stops, about three times that of household drivers. However, their average trip distance and parking duration are less than that of household drivers, 9.7 km and 2.12 hours respectively. As taxi cruise on the road to hunt clients, the use of the taxi is the heaviest. On average, taxi drivers travel 205.3 km in 8.5 hours in a day. They perform 10.6 trips with average trip distance 19.4 km. Their average parking duration is 1.46 hour, much less than those of household and ridesourcing drivers. From household to ridesourcing to taxi, vehicle use becomes more and more intense.

Daily Travel. Daily travel distance distributions are shown in Figure 2. This figure illustrates that many household drivers travel less than 50 km in a day. The aggregated household travel is well fit by the normal distribution with $\mu = 18.20$ km and $\sigma = 29.11$ km. Regarding taxi drivers, their aggregated daily travel distances is well fit by the normal distribution with $\mu = 196.29$ km and $\sigma = 98.32$ km. These results verify the randomness behind the daily travels of household and taxi drives. In terms of ridesourcing drivers, they pickup and drop off clients and, therefore, increase the shareability of vehicles (Vazifeh et al., 2018). Their daily travel distribution shifts to longer distances. Figure 2b shows ridesourcing drivers' daily travel distance follows a mix of the normal distribution with $\mu = 122.40$ km and $\sigma = 104.17$ km, and the exponential distribution with λ=0.0398. The weights of these two distributions are $\omega = 0.9944$ and $1 - \omega = 0.0056$ respectively, suggesting the normal distribution component mainly represents long-distance travel while the exponential distribution component emphasizes at short-distance travel.

Figure 3 shows the distribution of daily travel time and parking durations of ridesourcing and taxi drivers. As recorded household GPS trajectories are not continuous in time, we do not present the distributions of daily traveling and parking time of household drivers. Figure 3a shows that ridesourcing drivers have two travel time peaks: 1 hour and 7 hours. Correspondingly, the peaks of parking duration appear at 17 hours and 23 hours. Seventeen percent of ridesourcing drivers provide less than two hours of travel service in a day. A few (5.7 percent) drivers travel more than 12 hours per day. These results confirm the part-time commitment of ridesourcing drivers. Regarding taxi, daily travel time, and parking duration of drivers in this group have only one peak, at 7 hours and 17 hours respectively. Regarding taxi drivers, 3.9 percent travel fewer than two hours in a day and 16.9 percent of them provide travel service on the road more than 12 hours in a day.

Taking household travel as the benchmark, these results demonstrate that ridesourcing drivers and taxi drivers travel more to provide flexible on-demand mobility services in

Table 2. Descriptive statistics for Beijing household, ridesourcing, and taxi (this work) vehicle datasets

	Household	Ridesourcing	Taxi
Mean daily travel distance (km)	46.4	129.4	205.3
Mean daily travel time (hr)	1.8	5.7	8.5
Mean daily travel count	3	9.0	10.6
Mean trip distance (km)	13.7	9.7	19.4

Sources: He et al., 2016; Tu et al., 2019.

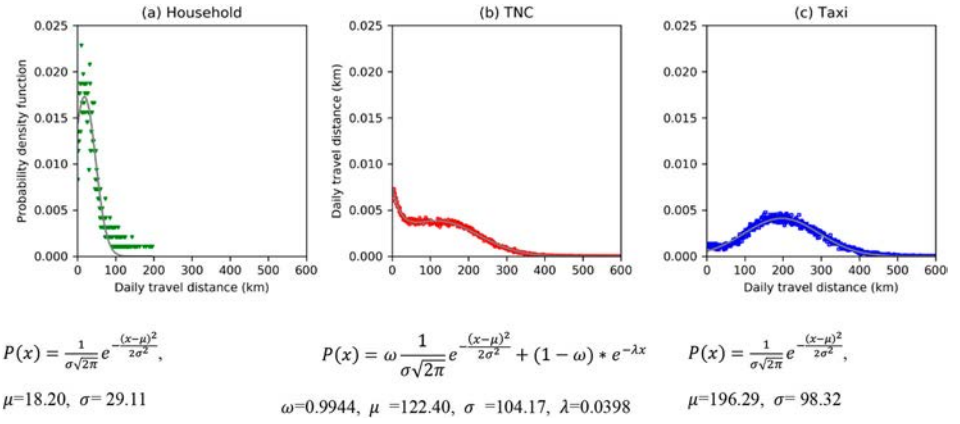

Figure 2. Distribution of daily travel distance: (a) household drivers, (b) transportation network company drivers, (c) taxi drivers

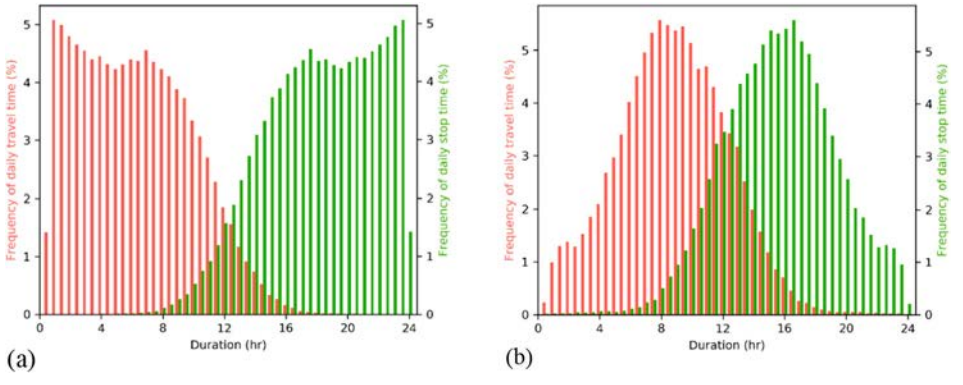

Figure 3. Distribution of daily travel time (red) and parking time (green) for: (a) ridesourcing drivers (taken from Tu et al., 2019: Copyright Elsevier, 2019) and (b) taxi drivers (this study)

Beijing. Ridesourcing drivers generally travel less than professional taxi drivers. Many ridesourcing drivers just provide travel service during rush hours or nighttime, such as 7:00–9:00, 17:00–19:00, 20:00–23:00. In general, ridesourcing fills the market gap between private travel and taxi travel, which imply different mobility patterns and future electrification potentials.

Trip Length. Distributions of travel distance segmented by a minimum of one-minute parking are shown in Figure 4. As seen from the figure, all three types of travel are well described by the exponential law. The similarity of these exponential laws suggests that daily ridesourcing and taxi travel typically serve a mix of individual travels. In general, ridesourcing and taxi drivers cruise on the road and pick-up and deliver clients; therefore, their daily travel connects multiple individual trips, which agrees with a potential for shareability of vehicles (Vazifeh et al., 2018). The exponential coefficients of household, ride-sourcing, and taxi travels are 0.0583, 0.1060, and 0.0617, respectively. These

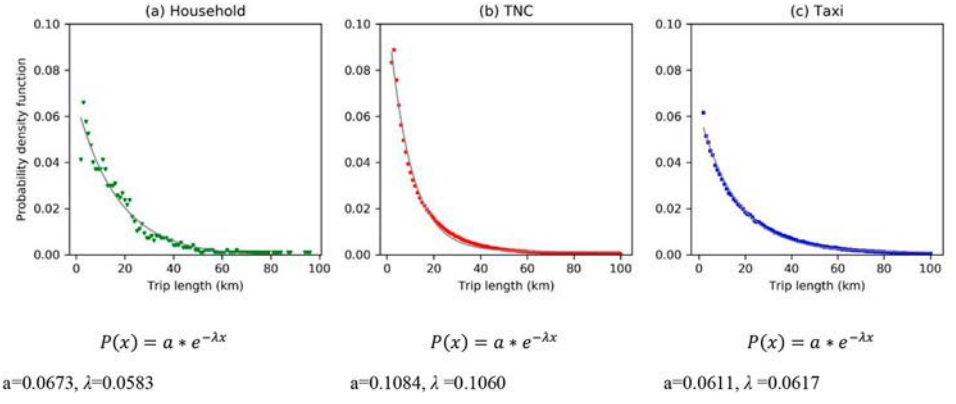

Figure 4. Distribution of trip length for (a) household, (b) ridesourcing, and (c) taxi drivers

coefficients demonstrate that ridesourcing drivers have a preference for short distance travel, which is consistent with the observation that many ridesourcing drivers just accept one short-distance trip for a passenger during their commute. On the other hand, household drivers perform more long-distance trips because of the poor job–housing balance in Beijing, which results in a relatively long household commuting distance. Taxi drivers tend to do long-distance trips to gain more revenue, especially to the airport and high-speed railway stations.

The Acceptance Ceilings

This section describes the electrification potential of three types of urban mobility. Following the approach of Tamor et al. (2013), He et al. (2016), and Tu et al. (2019) three types of trips segmented by short- (0.5 hour), medium- (four hours), and long-term (eight hours) parking are derived. For example, when the short-term parking (0.5 hour) is considered, two sequential trips with less than 0.5 hour parking will be re-connected as one trip. For a given EV driving range, the corresponding EV acceptance is evaluated and compared.

Figure 5 displays the frequency of trip length and the upper limit of EV acceptance ratios with charging available at all short-term parking events. Compared to what we see in Figure 4, the distribution of trip length shifts to long trips as short stops between trips are eliminated. Figure 5 shows that the frequency of trip length smoothly decays with distance. Fifty percent of household trips are less than 14 km; 50 percent of ridesourcing trips are less than 38 km; and 50 percent of taxi trips are less than 33 km. Almost all household trips (98.6 percent) are less than 100 km. But 14.6 percent of ridesourcing and 15.4 percent of taxi trips exceed 100 km. These trip distance distributions suggest different EV acceptances for the different driver groups. Household drivers are the most likely to accept short-distance EVs, while ridesourcing and taxi drivers would prefer long-distance EVs. For example, if fully charged, an EV with all-electric range (AER) of 200 km (EV200) can cover all the trips for household vehicles. For ridesourcing, it can fulfill the driving needs of 97.8 percent of trips. For a taxi driver, the EV200 is able to cover 98.7 percent of trips. Given ubiquitous high-speed charging infrastructure, an EV200 would be highly acceptable for household, ridesourcing, and taxi use.

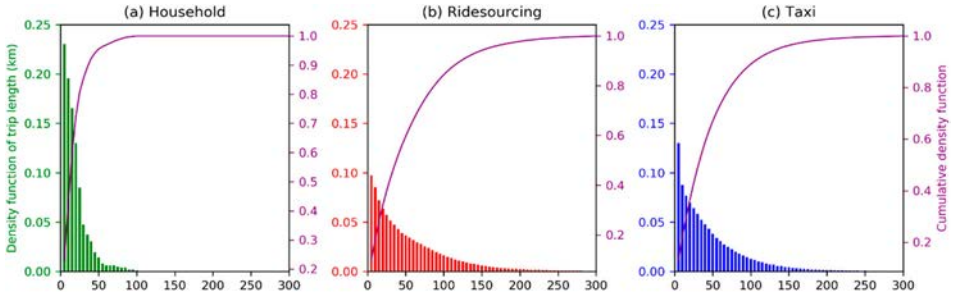

Figure 5. Frequency and cumulative distribution function of trip length between short-term parking (0.5 hours) events for (a) household vehicles, (b) ridesourcing vehicles, and (c) taxis

Figure 6 displays the spatial distribution of short-term parking for ridesourcing and taxi vehicles. The parking pattern for household vehicles is not reported due to the limited number of drivers in the dataset. Figure 6 shows several ridesourcing parking centers; the Beijing International airport (A), Beijing South Railway Station (B), Beijing West Railway Station (C), central business area at the East 2nd ring (D), Wangjing (E), Yiheyuan (F), and Yuyuantan (G). Many short-time parking events occur at these places. Parking for taxis is more spatially concentrated at the airport (A) and railway stations (B and C), Wudaokou (H), and Sanyuanqiao (I). This may reflect parking preferences for driver resting or vehicle handover. Fast charging stations (more than 30 kW) built at these clusters would support the electrification of ridesourcing and taxi travel in Beijing.

Considering the medium-term parking scenario in which fast charging is available wherever a vehicle is parked for four hours, Figure 7 shows the frequency of trip length and the corresponding acceptance ratio. As short-time parking is merged, the trip length becomes longer. The maximum length of ridesourcing and taxi trip reaches

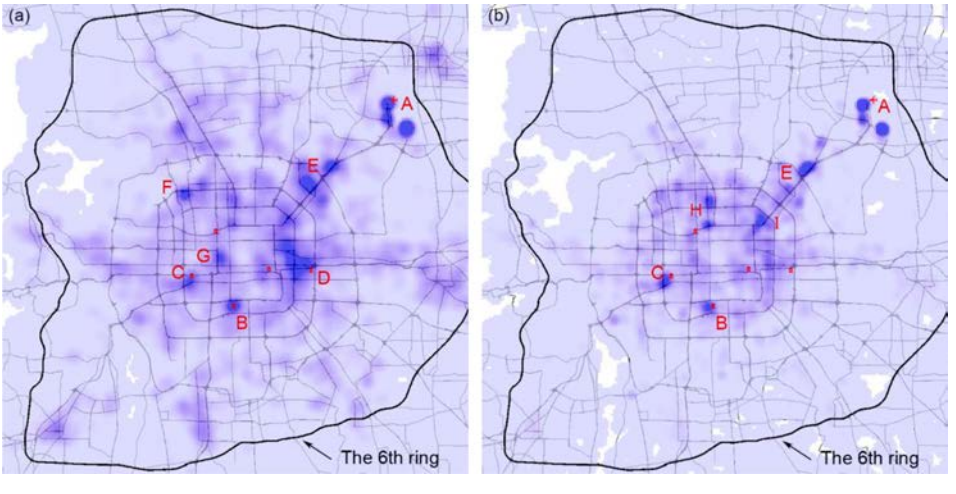

Figure 6. Spatial distribution of short-term parking events for (a) ridesourcing drivers, and (b) taxi drivers

500 km. Compared to the ubiquitous short-term parking, the fast charging scenario, given EVs with the same driving range, the acceptance ratio is significantly lower. In terms of household travel, EV200s can cover 98.6 percent of household trips. However, EV200 support just 77.1 percent of ridesourcing trips and only 57.7 percent of taxi trips. When the EV driving range is increased to 300 km, the acceptance rates for ridesourcing drivers and taxi drivers are 95.1 percent and 85.1 percent, still lower than those with ubiquitous charging (>99 percent).

Figure 8 displays the spatial distribution of medium-term parking. Compared to Figure 6, Figure 8 shows that ridesourcing parking is more spatially scattered because most ridesourcing drivers are part-time. Many ridesourcing drivers just provide on-demand mobility service in rush hours and park mainly at their home or workplaces. Clusters of medium-term parking of ridesourcing vehicles appear at the Beijing International Airport (A), Beijing South Railway Station (B), Beijing West Railway Station (C), central business area at the East 2nd ring (D), Wangjing (E), Wudaokou (H), and Sanyuanqiao (I). For taxis, there are clusters at Beijing West Railway Station (C), Wangjing (E), Wudaokou (H), and Sanyuanqiao (I). The parking at Beijing South Railway Station, Beijing West Railway Station, and Beijing International Airport are not as concentrated as those in Figure 6b. These patterns of parking actions demonstrate that, if current fuel vehicles are replaced by EVs with a medium charging rate, the demand for the distribution of charging situations will differ. Medium-rate charging points for ridesourcing vehicles should be widely distributed, while for taxis they should be more concentrated.

Figure 9 displays the frequency of trips segmented by long-time parking and the corresponding acceptance ratio. The length of all three types of trips becomes even longer. There are two parking peaks. The first peak appears at the shortest distance 5 km. While the other peaks of household, ridesourcing, and taxi travels appear at 15, 160, and 190 km, respectively. Consequently, the acceptance ratio further decreases. EV200 still covers 98.6 percent of household trips but only 58.1 percent of ridesourcing and 48.7 percent of taxi trips. If only slow-charging points are available, more than 50 percent of taxi drivers cannot accept the EV200 unless they are willing to reduce their daily travel.

Figure 10 shows the spatial distribution of long-term parking for ridesourcing and taxi drivers. When compared to the above short-term and medium-term parking, there are several new local parking centers of ridesourcing drivers between the fifth ring and the

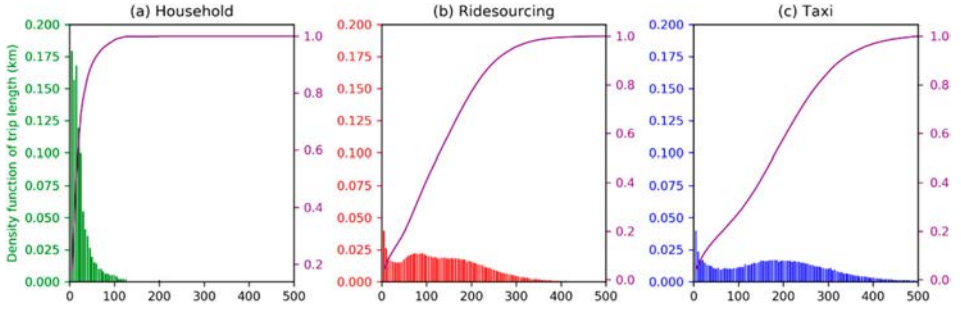

Figure 7. The frequency and the cumulative distribution function of trip length between medium-term parking (4 hours): (a) household vehicles, (b) ridesourcing vehicles, (c) taxis

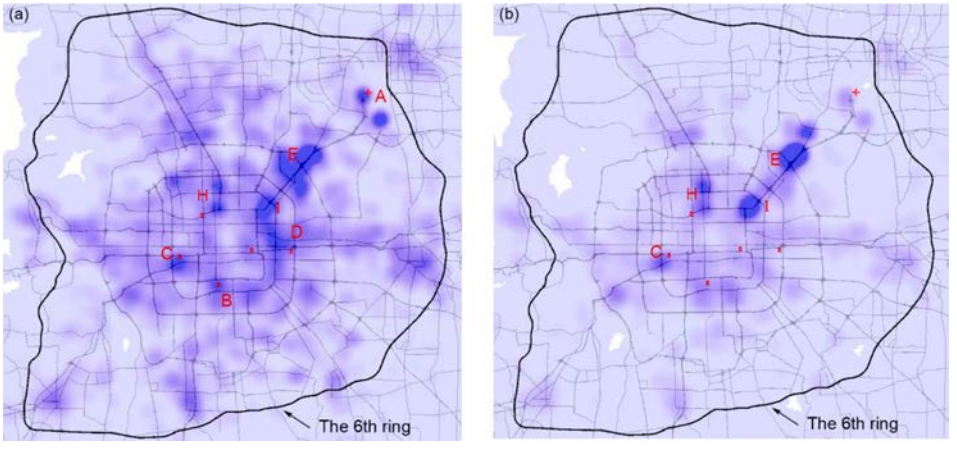

Figure 8. Spatial distribution of ubiquitous parking actions: (a) ridesourcing drivers and (b) taxi drivers

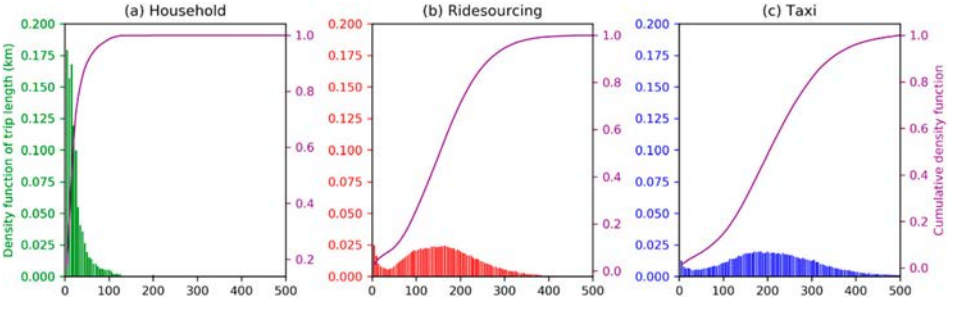

Figure 9. Distribution of trip length with long-time-parking (8 hours): (a) household vehicles, (b) ridesourcing vehicles, (c) taxis

sixth ring. Long-term ridesourcing parking is further spatially scattered, as the home of ridesourcing drivers are scattered in the city. When compared to medium-term parking in Figure 8b, the spatial distribution of taxi parking does not change too much. The parking clusters appear at the Beijing West Railway Station (C), Wangjing (E), Wudaokou (H), and Sanyuanqiao (I), which is in agreement with the driving habits of taxi drivers.

Discussion and Conclusion

Transportation is undergoing a revolution in electric, autonomous, connected, and shared mobility, and there are promising opportunities for smart future cities. Ridesourcing connects drivers and travelers via mobile applications. We build upon our previous work (Tamor et al., 2013; He et al. 2016; Tu et al., 2019) by providing a big-data analysis of the need of infrastructure and electrification potentials of typical urban travel modes. Multi-temporal resolution ridesourcing travel trips are extracted from raw GPS trajectories using machine learning. Mobility patterns of three typical urban (including household, ridesourcing, and taxi) travel modes are modeled and compared. Their electrification

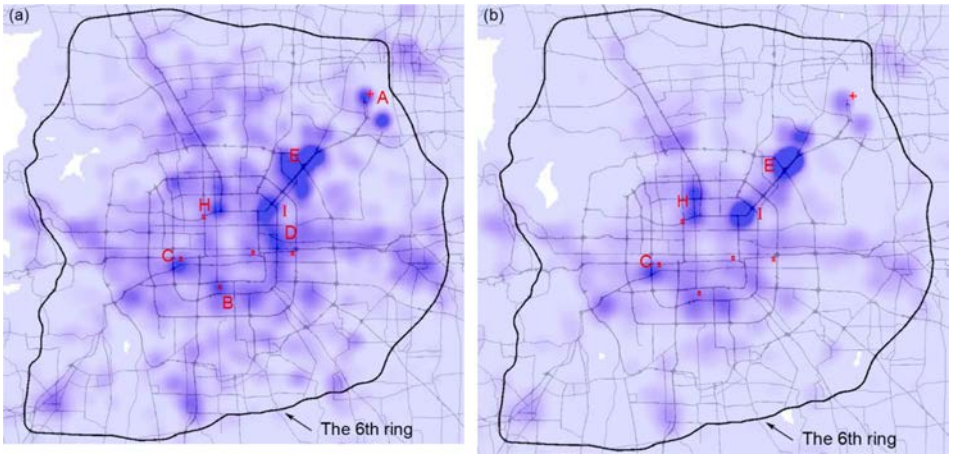

Figure 10. Spatial distribution of ubiquitous parking actions: (a) ridesourcing drivers and (b) taxi drivers

potentials are evaluated by considering travel distance, EV driving range, and parking durations. The case study in Beijing with 459 private cars, 144,867 ridesourcing vehicles, and 44,454 taxis demonstrate that household, ridesourcing, and taxi travel patterns are similar at the level of a single trip and they all follow an exponential distribution. However, they differ when total daily vehicle travel is considered and for an EV with a given driving range, the general EV acceptance decreases from household to ridesourcing to taxi use. Finally, the spatial distributions of potential charging infrastructures for the three typical urban travel modes (i.e., household, ridesourcing, and taxi) are different.

These findings have direct implications for future urban mobility. First, the goals of a high utilization of ridesourcing services and a high penetration of electric vehicles are in some conflict and need to be carefully balanced. The results of taxi use demonstrate that intense use of shared vehicles leaves little time for recharging and reduces the electrification potential regardless of EV driving range and available charging infrastructure. Second, spatial distributions of parking places demonstrate that charging infrastructure should be carefully deployed to fulfill the potential charging demands of different types of mobility. To encourage a shift to electric ridesourcing travel or electric taxi travel, high-speed charging points should be built firstly at the airport, railway stations, business districts, and high-technology parks, while low-speed charging points could be placed elsewhere (Tu et al., 2019).

This study provides a basis for future research into vehicle electrification for ridesourcing services. For example, the electrification potential is evaluated considering mobility patterns and EV driving range, thus representing a theoretical bound to EV acceptance. The socio-economic characteristics of ridesourcing drivers and taxi drivers, such as age, gender, and car-ownership, and preferences for EVs need to be considered in future work.

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Notes on Contributors

Wei Tu is an associate professor of Guandong Key Laboratory for Urban Informatics, Shenzhen Key Laboratory of Spatial Smart Sensing and Services, and Research Institute of Smart Cities, and Department of Urban Informatics, School of Architecture and Urban Planning, Shenzhen University.

Paolo Santi is a principal research scientist of Senseable City Laboratory, Massachusetts Institute of Technology. He is a research director at the Istituto di Informatica e Telematica del CNR.

Xiaoyi He is a postdoctoral research fellow at the Center for Sustainable Systems (CSS), School of Environment and Sustainability (SEAS), University of Michigan.

Tianhong Zhao is a Ph. D student in the Department of Urban Informatics, School of Architecture and Urban Planning, Shenzhen University.

Xianglong Liu is a professor at the China Academy of Transportation Sciences and vice director of the Key Laboratory. on Advanced Public Transportation System (APTS) of MOT.

Qingquan Li is a professor of Guandong Key Laboratory for Urban Informatics, Shenzhen Key Laboratory of Spatial Smart Sensing and Services. He is the president of Shenzhen University.

Timothy J. Wallington is a senior technical leader in the Research and Advanced Engineering organization at Ford Motor Company.

Gregory A. Keoleian is a Peter M. Wege Endowed Professor of Sustainable Systems and director and co-founder of Center for Sustainable Systems, School of Environment and Sustainability, University of Michigan.

Carlo Ratti is professor of the practice and director of MIT Senseable City Laboratory.

ORCID

Wei Tu http://orcid.org/0000-0002-0255-4037
Paolo Santi http://orcid.org/0000-0002-8942-8702
Xiaoyi He http://orcid.org/0000-0002-6263-0329
Timothy J. Wallington http://orcid.org/0000-0002-9810-6326

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