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Comprehensive comparison of e-scooter sharing mobility: Evidence from 30 European cities

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A R T I C L E I N F O

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A B S T R A C T

Although e-scooter sharing has become increasingly attractive, little attention has been paid to a comprehensive comparison of e-scooter sharing mobility in multiple cities. To fill this gap, we conduct a comparative study to reveal the similarity and difference of e-scooter sharing mobility by collecting and analyzing vehicle availability data from 30 European cities during post COVID-19 pandemic. The comparisons are implemented from four perspectives, including temporal trip patterns, statistical characteristics (i.e., trip distance and duration), utilization efficiency, and wasted electricity during idle time. Results suggest that the similarity and difference co-exist between e-scooter sharing services in the cities, and utilization efficiency is significantly related with the number of e-scooters per person and per unit area. Surprisingly, on average nearly 33% of electricity are wasted during idle time in these cities. These research findings can be beneficial to further optimizing e-scooter sharing mobility services for transportation planners and micro-mobility operators.

1. Introduction

In recent years, electric scooter (e-scooter) sharing, as a type of shared micro-mobility, has become increasingly popular in many cities worldwide (Liu et al., 2019; Caspi et al., 2020; Hosseinzadeh et al., 2021b). In combination with bike-sharing, the use of two types of shared micro-mobility services has positive effects on transportation and environment by solving the first- and last-mile problem and producing less transport-related emissions compared to motor-based vehicles (Otero et al., 2018; Zhang and Mi, 2018; Baek et al., 2021; Gao et al., 2021a; Ortúzar, 2021; Li et al., 2021a). Unlike docked bike-sharing, the usage of the e-scooter sharing is more flexible since users are not restricted to pick-up and drop-off at fixed stations. In contrast to dockless bike-sharing, e-scooters are easier to carry due to their smaller size. For example, it is common that users take e-scooters to trains or supermarkets. Even though e-scooter sharing services were first introduced in 2017 and much later than bike-sharing, e-scooter sharing has also experienced rapid expansion and development in the past four years (McKenzie, 2020; Luo et al., 2021).

With the introduction of this new transport mode in more cities, e-scooter regulations have been surging across the world and particularly in Europe to embrace micro-mobility (Møller et al., 2020). For instance, users must comply with the regulations

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formulated by Swiss Federal Agency for Roads while riding e-scooters in Switzerland, such as controlling the maximum speed, wearing a helmet, etc.[1] In addition, the emergence of e-scooters also poses new challenges in cities, such as how to improve the usage efficiency of e-scooters that operators care more about, electricity consumption issues of e-scooters, or setting up infrastructures to reduce visual pollution (e.g., e-scooters are parked or thrown randomly all over the city). While establishing regulations or dealing with the aforementioned challenges, it is important to understand e-scooter sharing mobility patterns to make better decisions.

A strand of studies on shared e-scooters based on trip data from micro-mobility operators is continuously emerging. For instance, spatial and temporal patterns of e-scooters (Jiao and Bai, 2020; McKenzie, 2020; Zhu et al., 2020; Hosseinzadeh et al., 2021b; Zhao et al., 2021; Wang et al., 2021), shared e-scooter usage and its influencing factors (Bai and Jiao, 2020; Caspi et al., 2020; Huo et al., 2021; Hosseinzadeh et al., 2021a; Merlin et al., 2021), how e-scooters competing or complimenting with other transport modes (Gebhardt et al., 2021; Luo et al., 2021; Reck et al., 2021) have been investigated using data in different cities. Despite there are already several studies that examine e-scooter sharing mobility patterns, they are normally conducted based on data from few cities. Until now, there is no research to comprehensively and systematically compare the mobility patterns of shared e-scooters from multiple cities in different countries. Considering the variety of urban characteristics (city size, built environment, socioeconomic) across cities, the e-scooter sharing mobility patterns could vary across cities. Therefore, it is significant and necessary to conduct a comparison study to reveal the similarity and difference of e-scooter sharing mobility patterns by extracting evidence from many different cities, thereby obtaining more reliable, robust, and transferable results and conclusions to support decision making in transportation.

To fill this research gap, we collect vehicle availability data from shared e-scooter systems in 30 European cities, and explore e-scooter sharing mobility patterns in terms of four aspects, namely temporal distribution of trips, statistical distribution of mobility descriptors, usage efficiency of e-scooters, and battery charge. In this context, four specific research questions (RQ) outlined below will be addressed in the remainder of this work:

- **RQ1:** What are the similarities and differences of temporal patterns of e-scooter trips in different cities?
- **RQ2:** What are the similarities and differences of the mobility descriptors (e.g. trip duration, trip distance) of e-scooter sharing in different cities?
- **RQ3:** What are the characteristics of utilization efficiency of shared e-scooters across different cities?
- **RQ4:** What are the patterns of wasted electricity of shared e-scooters during idle time across different cities?

To answer these questions, we first apply a trip identification method to extract trips from the collected vehicle availability data. Then, a series of indicators are calculated based on the trips, including trip volume, trip duration, trip distance, trip speed, time to booking, and state of charge (SOC) of battery. Lastly, a comparative analysis is implemented to understand e-scooter sharing mobility patterns by exploring the distribution and characteristics of the indicators and examining their similarities and differences.

The rest of the paper is organized as follows. Section 2 reviews the spatio-temporal patterns of e-scooter sharing services. Section 3 briefly describes the utilized e-scooter data. The methodologies of this paper are introduced in Section 4. Section 5 presents the results of this study. Then, Section 6 discusses the key findings and policy implications. Finally, we summarize and highlight our conclusions in Section 7.

2. Literature review

The increasing availability of trip data and vehicle availability data from micro-mobility operators have led to a large quantity of studies on e-scooter sharing mobility patterns. However, little attention has been paid on uncovering these patterns by extracting evidence from multiple cities in different countries.

Research in the first strand focuses on understanding spatiotemporal patterns of e-scooter usage. For instance, Mathew et al. (2019) analyzed the temporal usage patterns of e-scooter using the trip data over three months in the City of Indianapolis. It was found that the peak usage periods were between 4:00–9:00 p.m for weekdays and between 2:00–7:00 p.m for weekends. Jiao and Bai (2020) investigated the spatial and temporal patterns of shared e-scooters in Austin by analyzing how the monthly trip count, total vehicle miles traveled, average trip distance, and average operation time change over time and generating heatmaps of e-scooter usage via spatial analysis. McKenzie (2020) identified the differences between different micro-mobility services, including e-scooter sharing and dockless e-bikes sharing services, from spatial and temporal perspective by using the micro-mobility data in Washington, D.C. Zhu et al. (2020) conducted a comparative analysis between bike-sharing and scooter-sharing activities in Singapore to understand spatiotemporal heterogeneity of two micro-mobility services. By exploring the spatial–temporal distribution of two micro-mobility services, the similarities and differences between the two sharing services were discovered in the study area. Zou et al. (2020) conducted an exploratory analysis of the travel patterns and behaviors related to e-scooter using the data in Washington, D.C. Zhao et al. (2021) investigated the impact of data processing on deriving micro-mobility patterns from vehicle availability data by conducting a case study on e-scooter sharing in Zurich. The temporal distribution analysis results indicated that the usage of shared e-scooters displayed different patterns on weekdays and weekends.

Another group of studies explored how the usage of e-scooter sharing is influenced by various factors. For example, Bai and Jiao (2020) conducted a comparison study of Austin and Minneapolis to investigate dockless e-scooter usage patterns and their relationships with urban built environments. Caspi et al. (2020) explored how the built environment, land use, and demographics

[1] https://healthyandsafe.biz/e-scooters/.

Table 1
Literature review exploring e-scooter sharing mobility patterns.

Study	Study area	Research findings	Relevance
Mathew et al. (2019)	Indianapolis	• Peak usage periods were between 4:00–9:00 p.m. on weekdays, and between 2:00–7:00 p.m. on weekends. • The scooter usage was quite low during the morning hours of the day.	RQ1 and RQ2
Jiao and Bai (2020)	Austin	• The average trip distance and duration were 0.77 miles and 7.55 min. • The riders tended to use e-scooters from 8 a.m. on weekdays and 11 a.m. on weekends.	RQ1 and RQ2
McKenzie (2020)	Washington D.C.	• The six e-scooter sharing services show similar temporal activity behavior. • The core regions of the six micro-mobility services focus on downtown.	RQ1 and RQ2
Zhu et al. (2020)	Two districts in Singapore	• The two districts show different usage pattern. • A larger number of e-scooter trips can take 5 to 8 min.	RQ1 and RQ2
Zou et al. (2020)	Washington D.C.	• The median trip distance was 0.73 mile and median duration was 9.65 min. • The trips are mostly concentrated during the middle of the daytime hours.	RQ1 and RQ2
Zhao et al. (2021)	Zurich	• The usage displays three peaks on weekday and one peak on weekend.	RQ1 and RQ2
Bai and Jiao (2020)	Austin and Minneapolis	• The temporal usage pattern varied largely between cities. • Minneapolis riders tended to ride longer.	RQ1 and RQ3
Caspi et al. (2020)	Austin	• The usage of e-scooters is associated with areas with high employment rates and with bike infrastructures.	RQ3
Heumann et al. (2021)	Berlin	• The e-scooter usage is related to points of interest. • Temporal peaks of usage differ by point of interest category.	RQ1 and RQ3
Hosseinzadeh et al. (2021a)	Louisville	• The related factors of usage include land use, high employment, walkability, bikeability and access to public transit, etc.	RQ3
Huo et al. (2021)	Austin, Minneapolis, Kansas City, Louisville, and Portland	• The temporal variation of ridership of different cities exhibits similar pattern. • The ridership is positively correlated with population density, employment density, etc.	RQ1 and RQ3

affect e-scooter sharing usage using spatial regression techniques. Heumann et al. (2021) investigated how the built environment and land use affect e-scooter trips by implementing temporally and spatially resolved trip pattern analyzes The work by Hosseinzadeh et al. (2021a) utilized the e-scooter data between November 2018 and February 2020 in Louisville, Kentucky to examine spatial factors associated with scooter trips. The results reported that the urban center, downtown, and few surrounding areas have a higher density of trips. Huo et al. (2021) examined the influence of the built environment on E-scooter sharing ridership in five cities of the U.S., namely Austin, Minneapolis, Kansas City, Louisville, and Portland.

We summarized the literature to show their relevance on this study, as shown in Table 1. The fourth column shows their relevance on the research questions of this research. In summary, these studies on e-scooter sharing are limited to a single city or country. Although trip data is increasingly available from micro-mobility operators, there is not yet research that systematically compares the e-scooter sharing mobility patterns from multiple cities in different countries. The usage patterns of e-scooters can be influenced by a wide variety of factors (e.g., cultural, economic) across different cities (Fishman, 2015; Kon et al., 2021). Hence, it is important and necessary to bridge this gap.

3. Study area and data description

In this study, we collect the vehicle availability data of e-scooter sharing services from 37 programs across 30 cities in 8 Europe countries, including Austria, Finland, France, Germany, Italy, Norway, Sweden, Switzerland, as shown in Fig. 1. It can be observed that the data collection periods of these cities are mainly concentrated on April to July, 2021 that correspond to spring and summer in Europe. Since these cities were recovering from the COVID-19 pandemic during this period due to more and more people getting vaccinated, this work could be case studies in post COVID-19 pandemic. In addition, we also examine the influence of date ranges on micro-mobility indicators across these cities in the supplementary materials, as shown in Table S1.

These data are collected via the Application Programming Interface (API) provided by two operators. The vehicle availability data only record the information of e-scooters when they are not utilized, from which the origin and destination of each trip can be identified. At a given timestamp, each record has a series of items describing the status of an e-scooter, including e-scooter id, e-scooter location (longitude and latitude), timestamp, the state of charge (SOC) for the battery and other provided features. The SOC represents the level of the charge of e-scooter battery relative to its capacity. It is denoted by a number between 0 and 100 (%), where 0 represents the battery is empty and 100% represents the battery is fully charged.

Based on the collected vehicle availability data, the e-scooter trips are generated based on the method in Zhao et al. (2021). Each trip comprises the detailed information including e-scooter id, start and end location, start and end timestamp, start and end SOC, which can be expressed as a tuple $(vehicleid, stime, sloc, sSOC, etime, eloc, eSOC)$. However, it should be noted that some identified short trips might be fake due to the GPS positioning error. In addition, fake trips can also be caused when e-scooters are moved by the operators to collect and charge them. These fake trips are filtered out based on trip distance and duration in data processing. The description of the collected vehicle availability data in each city is listed in Table 2. Each record corresponds to one city, which

Fig. 1. The selected cities in this study.

includes the columns *country*, *city*, *population of city*, *start date* and *end date* of the data, *shared e-scooter fleet size* of the city, *trip number*, *filtering out ratio* and *service area*. The first five variables describe the basic information of the source data. The last four variables are calculated from the source data. The *shared e-scooter fleet size of the city* are counted by using the e-scooter *vehicleid*. The *trip number* denotes the number of remaining extracted e-scooter trips after cleaning the unreasonable trips. The filtering criteria are introduced in Section 4. The *filtering out ratio* is the proportion of the remaining e-scooter trips in all the extracted trips. The calculation method of *service area* is also introduced in Section 4.

4. Methodology

The workflow for the comparison study is developed, as shown in Fig. 2. First, a database is built to store the collected vehicle availability data from different cities. Next, data processing is implemented to identify trips from the vehicle availability data and filter out the outliers. Then, various indicators are calculated to model micro-mobility in terms of temporal trip distribution, statistical distribution, utilization efficiency, and wasted electricity of e-scooters during idle time. Last, the comparisons of micro-mobility patterns among 30 cities are summarized and analyzed from the above-mentioned four aspects.

Since the extracted trips only contain trip origin and destination, the actual trajectory of each trip is not available. Considering that the movement of e-scooter is restricted by road network, to estimate the trip distance more accurately, network distance between origin and destination is measured to approximate the actual trip distance. Concretely, the trip distance between each pair of origin and destination is estimated by using the GraphHopper API (https://www.graphhopper.com/), which is an open-source routing server written in Java and provides a web interface called GraphHopper Maps. Due to the large number of e-scooter trips in multi-cities, instead of using the online service, we utilize the offline service to estimate trip distances of all extracted e-scooter trips. GraphHopper constructs road network based on OpenStreetMap data and uses various algorithms (e.g., A* and Dijkstra) to find the optimizing paths for different transport modes (e.g., walking, bike, and car). For different modes, GraphHopper only allows certain types of edges to be added to the constructed network. Given that the e-scooter is light and similar to walking mode, we adopt walking as a replacement for e-scooter, which exclude the roads mainly for cars such as highways.

After calculating the network distance, the average trip speed for each e-scooter is calculated. The fake trips and outliers are removed based on several criteria. According to the existing studies (McKenzie, 2020), we remove the trips with a network distance shorter than 50 m and more than 10 km, and trip duration shorter than 60 s and longer than 1.5 h. Similarly, the trips with an average trip speed greater than 25 km/h are also removed. Considering that the battery will be discharged in a trip, the electricity at the origin should be higher than it is at the destination. So the trips whose start SOC is lower than the end SOC will be filtered out.

Table 2
The description of the vehicle availability data for shared e-scooters from each city.

Country	City	Population	Start date	End date	Shared e-scooter fleet size	Trip number	Filtering out ratio (%)	Service area (km^2)
Austria	Vienna	1 920 949	2021-05-24	2021-07-27	1686	180 900	76.66	135.49
Finland	Helsinki	656 920	2021-05-25	2021-07-25	7913	1 128 507	86.30	97.31
Finland	Tampere	341 696	2021-06-16	2021-07-27	2058	297 193	96.48	69.12
Finland	Turku	194 391	2021-06-16	2021-07-25	2030	255 091	96.57	61.81
France	Lyon	518 635	2021-05-24	2021-07-24	2478	280 399	78.04	56.57
France	Paris	2 175 601	2021-05-24	2021-07-25	8582	397 849	79.27	119.95
Germany	Berlin	3 664 088	2021-04-06	2021-07-28	22 948	1 889 075	83.92	337.47
Germany	Cologne	1 083 498	2021-05-24	2021-07-25	6472	183 534	74.83	138.38
Germany	Duesseldorf	620 523	2021-05-24	2021-07-26	2360	160 511	80.08	94.18
Germany	Frankfurt	764 104	2021-05-24	2021-07-27	3220	184 518	77.28	110.42
Germany	Hamburg	1 852 478	2021-05-24	2021-07-26	6729	603 678	86.98	247.91
Germany	Hannover	534 049	2021-05-24	2021-07-24	1974	188 937	79.46	140.83
Germany	Karlsruhe	308 436	2021-06-16	2021-07-29	1043	135 115	95.86	54.94
Germany	Muenster	316 403	2021-05-24	2021-07-28	1616	153 900	80.69	74.52
Germany	Munich	1 488 202	2021-04-06	2021-07-25	7476	845 464	89.65	164.40
Germany	Stuttgart	630 305	2021-06-16	2021-07-24	1775	159 044	93.65	96.08
Italy	Milan	1 397 715	2021-04-06	2021-07-26	1203	142 077	95.80	54.30
Italy	Rome	2 783 809	2021-04-06	2021-07-25	1077	112 790	94.31	49.85
Norway	Bergen	285 601	2021-06-16	2021-07-25	1958	195 844	93.85	55.21
Norway	Oslo	697 010	2021-04-06	2021-07-26	17 894	4 059 708	92.72	246.09
Sweden	Gothenburg	583 056	2021-05-14	2021-07-20	3550	728 451	95.53	87.32
Sweden	Lund	91 940	2021-05-25	2021-07-20	918	45 843	90.31	34.33
Sweden	Stockholm	975 551	2021-05-14	2021-07-21	14 405	1 739 791	94.75	139.74
Sweden	Uppsala	233 839	2021-05-14	2021-07-21	2349	230 056	93.34	71.30
Switzerland	Basel	173 775	2021-03-26	2021-07-25	517	66 997	89.48	31.18
Switzerland	Bern	134 727	2021-03-26	2021-07-25	469	49 983	89.67	33.07
Switzerland	Stgallen	76 183	2021-05-24	2021-07-25	796	61 019	83.46	26.06
Switzerland	Winterthur	114 211	2021-03-26	2021-07-25	119	17 905	96.13	17.13
Switzerland	Zug	30 927	2021-05-24	2021-07-25	184	11 631	72.56	13.00
Switzerland	Zurich	421 712	2021-03-26	2021-07-29	1816	256 472	89.23	76.71

4.1. Modeling temporal and statistical trip distribution

To examine the similarities and differences of temporal trip distribution, a trip frequency signature for each city is constructed to capture the temporal fluctuations of e-scooter trip frequency. Considering that the date ranges of the data are inconsistent and there happened to be a local special event during a particular time, the temporal signature is calculated for each city by aggregating the e-scooter trips based on the day of a week and the hour of a day. Trip frequencies on each weekday and weekend are obtained by calculating the average values of frequency on the corresponding weekdays or weekends respectively. Taking one hour as the temporal granularity, the signature S_i of a city is denoted as a 1×168 vector that covers the average trip frequency on each hour from Monday to Sunday:

$$S_i = [F_{1,1}, \dots, F_{j,k}, \dots, F_{7,24}] \tag{1}$$

where S_i^n represents the average trip frequency of the ith city. j is from 1 to 7 to the day of a week from Monday to Sunday, k is from 1 to 24 to indicate each hour of one day. Since the service area and shared e-scooter fleet size are diverse, the number of trips in each city is also various. Hence, the temporal signature in each city is normalized. Concretely, each element in the temporal signature vector is divided by the sum of all elements in the vector. The normalization is expressed as the following formula:

$$NS_i = \frac{[F_{1,1}, \dots, F_{j,k}, \dots, F_{7,24}]}{\sum_{j=1}^{7} \sum_{k=1}^{24} F_{j,k}} \tag{2}$$

Based on the constructed signatures, the similarity of temporal trip distribution among 30 cities can be measured. On the one hand, the similarity of temporal trip distribution between each pair of cities can be measured by calculating Pearson correlation coefficient of two signatures. On the other hand, these cities can be further clustered into different groups by using a bottom-up hierarchical clustering method. The Euclidean distance is used to measure the similarity between the normalized temporal signatures of cities. The Ward's method is to determine the pairwise distances between each pair of temporal signatures, which minimizes the variances of temporal signatures within a group (Ward, 1963). Hence, the ward method is chosen as the linkage criterion of hierarchical clustering.

To further uncover the statistical distribution pattern of e-scooter trips, it is necessary to model micro-mobility with indicators. In this study, two typical mobility descriptors, trip distance and trip duration, are adopted to examine the statistical characteristics of micro-mobility, which have been widely used in human mobility studies (Song et al., 2010; Liu et al., 2012; Zhao et al., 2017; Li et al., 2020c; Gao et al., 2021b).

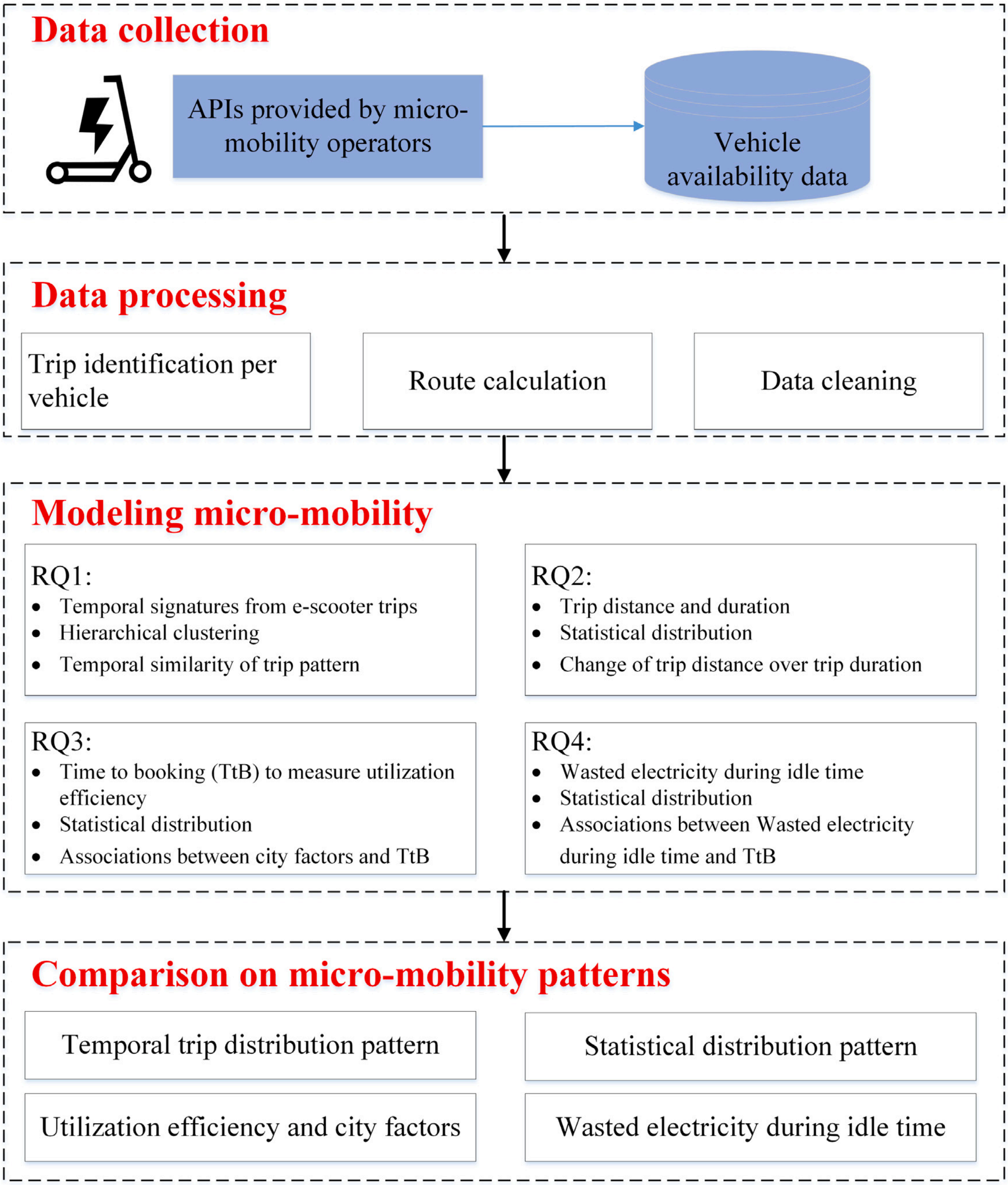
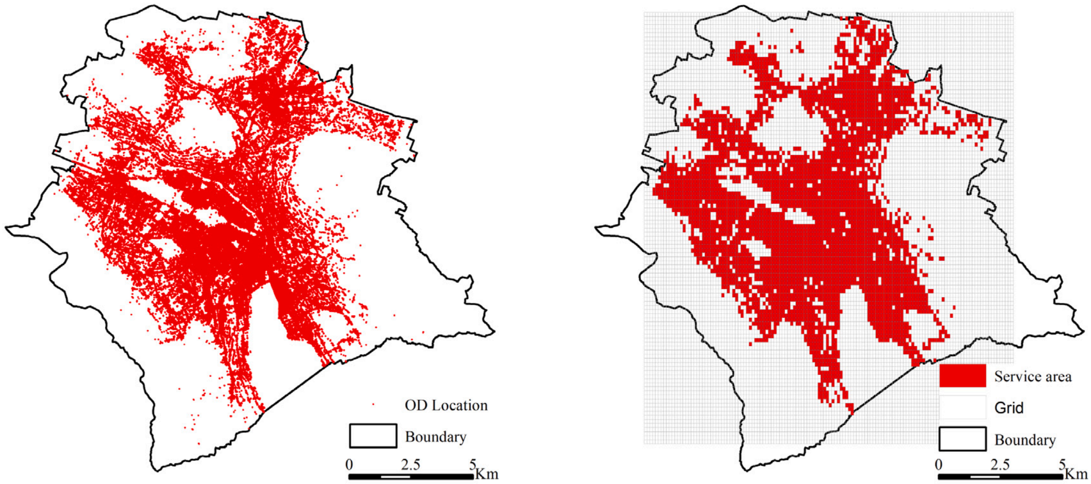


Fig. 2. The workflow for the comparison study.

4.2. Measuring utilization efficiency of e-scooters

Time to Booking (TtB) for an e-scooter represents the duration that the e-scooter is booked again after the previous trip has ended, which is employed to measure the utilization efficiency of e-scooters. TtB has been indicated to be more reasonable to measure the utilization efficiency of micro-mobility services in an area (Li et al., 2020b). To calculate the time to booking for each e-scooter, we first extract all pairs of consecutive trips for each e-scooter. Given a trip of an e-scooter, its consecutive previous trip cannot always be obtained due to various reasons (e.g., data quality). We only consider the trip whose start point is less than δ meters away from the end point of the previous trip. Here, $\delta = 50$ is adopted as the threshold according to Li et al. (2020b). The Time to Booking is



(a) Spatial distribution of OD points

(b) Service area of Zurich

Fig. 3. Example of service area for Zurich.

calculated as:

$$ST_{m,t} = S_{m,t} - D_{m,t-1} \tag{3}$$

where $S_{m,t}$ is the start time of the current trip for e-scooter m; $D_{m,t-1}$ is the end time of the previous trip for the same e-scooter. A bigger Time to Booking indicates an e-scooter is used after a long idle, which denotes a low efficiency.

Since the utilization efficiency of e-scooters among cities could be related to the characteristics of city, two basic explanatory variables, namely the population and city size are considered in this study, which are obtained via a statistical website.[2] However, it should be noted that the city area is generally not equal to the service area that micro-mobility operators provide, due to urban contexts (e.g., river, lake, mountain) and policy restrictions. Since the service area information from operations is not publicly accessible, a data-driven method is developed to calculate the service area for each city at a fine scale. Fig. 3(a) shows an example in Zurich, where black line represents the boundary of Zurich and the red points are locations of the origins and destinations of all e-scooter trips in Zurich. The real area where e-scooters appear in the city is represented as the service area. Considering that the origins and destinations of e-scooter trips already take into account the constraints of service areas provided by micro-mobility operators, the calculated service areas would more accurately reflect actual demand of users.

To calculate the service area, we divide the city into cells with 0.001 longitude × 0.001 latitude size (shown in Fig. 3(b)). The boundary of the grid is determined by the maximum and minimum value of the longitude and latitude of e-scooters. The number of origins and destinations within cell i is denoted as C_i. A larger C_i implies that the corresponding area is more popular for e-scooter riders. Considering that some cells containing few points could be caused by GPS error and parking accidentally, only the cells that contain origins and destinations more than a threshold will be considered to calculate the service area. Since the trip volume in each city is different, the threshold is defined as the $25th$ percentile of all C_i in that city.

4.3. Quantifying the electricity wasted during idle time of e-scooters

As an electric-powered micro-mobility service, e-scooter sharing is generally considered as an cleaner transport mode. However, when an e-scooter is idle and waiting for the next passenger, the e-scooter battery will be continuously discharging and consuming energy for other equipped devices (e.g., GPS, screen) without providing riding service for passengers. From the perspective of energy consumption and sustainability, the aforementioned electricity is wasted during idle time without bringing any benefits. In addition, reducing the wasted electricity of e-scooters is beneficial for lowering the operating cost of micro-mobility operators. Hence, it is necessary to quantify the wasted electricity of e-scooters.

To quantify how much electricity will be wasted in an e-scooter sharing program, we investigate the charging and discharging processes for all e-scooters in a city. An indicator is proposed to estimate such wasted electricity of e-scooters, which is called electricity wasted during idle time (EWDIT). The electricity wasted during idle time in each discharging process is estimated based on the wasted electricity divided by the total discharged electricity in the whole process. Since the actual electricity of the battery at one moment is unknown, the EWDIT is calculated by using the change of state of charge (SOC) of the battery as the replacement.

[2] https://www.citypopulation.de/Europe.html.

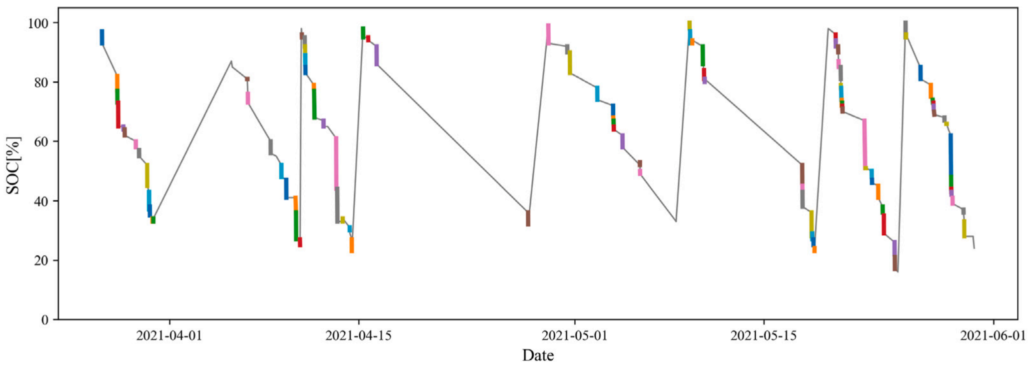


Fig. 4. Example of SOC of the battery for an e-scooter. The lines with different colors (excluding gray color) represent the trip. The gray lines from a lower SOC to a higher SOC represent charging process or the battery is changed. The gray lines among the trips represent discharging process without providing any service. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

As shown in Fig. 4, the gray line from a lower SOC to a higher SOC indicates that the charging process of one e-scooter is completed by the operator. The consecutive colored line from a higher SOC to a lower SOC implies the discharging process, which generally covers the electricity consumption of several trips. The electricity wasted during idle time can be denoted as

$$EWDIT = 1 - \frac{\sum_{i \in DC} sSOC_i - eSOCi}{sSOC_{DC} - eSOC_{DC}} \tag{4}$$

where DC represents a discharging process; i denotes the ith trip occurred in the discharging process; $sSOC_{DC}$ and $eSOC_{DC}$ are the SOC of the start and end of the discharging process, respectively; $sSOC_i$ and $eSOCi$ are the start SOC and end SOC of ith trip contained in the charging process.

To recognize the discharging process, all the trips for each e-scooter in each city are sorted chronologically. Then, these trips are divided into different groups at where the SOC of the trip start is higher than that of the previous trip end. Each group is a discharging process of the e-scooter. According to all the recognized discharging processes, the SOC of batteries at the beginning are generally higher than 90%, and the batteries will be recharged or replaced at the level between 20% and 35%. Thus, the discharging processes where the start of SOC is lower than 90% and the end of SOC is higher than 35% are filtered out.

5. Analysis and results

In this section, comprehensive analyzes are performed to compare the micro-mobility patterns among the selected 30 cities in terms of the proposed four research questions.

5.1. Temporal trip distribution

In addressing **RQ1**, we construct the temporal signatures based on e-scooter trips for these cities, as introduced in Section 4.1. The detailed temporal signatures of e-scooter service in these cities are shown in Figure S1 of supplementary material.

If we scrutinize the temporal signatures of e-scooter trips in these cities, the similarity and difference between these cities can be assessed by using Pearson correlation coefficient and clustering. As shown in Fig. 5, it displays the results from two aspects, namely clustering and similarity matrix. The first part uses a dendrogram to show the hierarchical relationship between cities and determine the clusters by setting a threshold. Each branch corresponds to one city. Concretely, the structure of the clusters is generated using a hierarchical clustering method based on the normalized temporal signatures. Since the clustering method is hierarchical, which means different distance thresholds can produce different clustering results. Here, according to the visualization result, we select the threshold shown as the blue line in Fig. 5 and generate seven clusters. Accordingly, these cities can be divided into different groups contained in different black rectangles, which are denoted as $[Br_1, Br_2, \dots, Br_7]$ from the left to the right. The second part is shown in a similarity map, each cell represents the similarity score calculated by the Pearson correlation coefficient between two cities. It is essentially 30×30 matrix denotes the similarity between two cities regarding temporal trip distribution. Since the similarity matrix is symmetric, each row or column in the similarity map represents the similarities between a given city and other cities. The elements in the diagonal depict the coefficient between one city and itself, which are always one. The two results are displayed in one figure since both results can measure similarity between these cities from different perspectives. And the two results can be proof for each other. For instance, the cells within the black bounding box depict the similarities of the corresponding cities. Besides, the involved cities in the black bounding box have higher similarity with each other in terms of temporal trip distribution compared with the cities in other black bounding boxes. Each black bounding box corresponds to one cluster in the dendrogram.

To display the similarities and the disparate patterns of clusters, the normalized temporal signatures of cities in each cluster and the average normalized temporal signatures of 30 cities are illustrated in Fig. 6. The average normalized temporal signatures

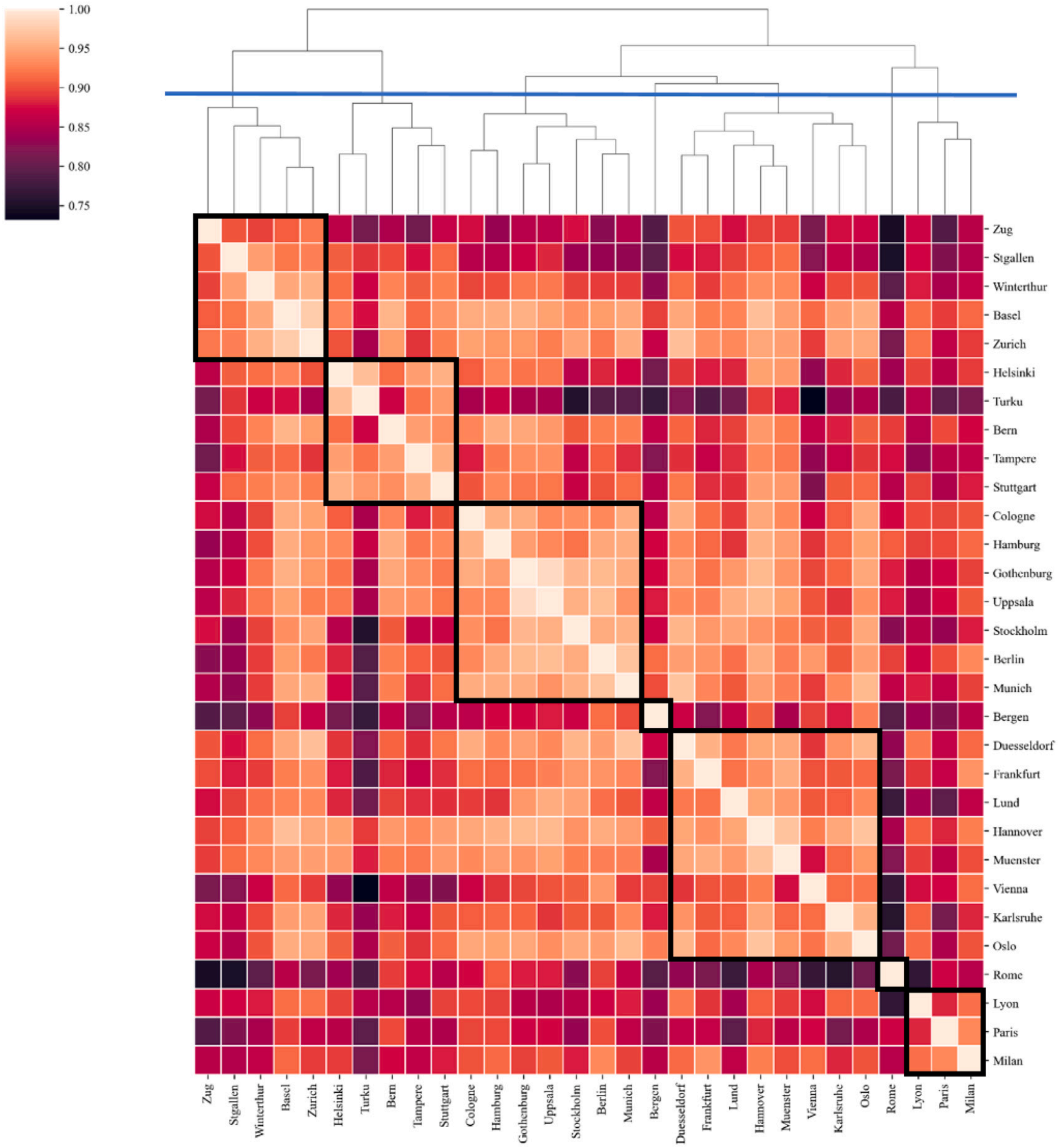


Fig. 5. The similarity matrix and hierarchical clustering of temporal signatures for e-scooters in these cities. The blue line denotes the threshold line of the hierarchical clustering. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

of 30 cities is represented by the black line, which is the same across the seven clusters. As shown in Fig. 6, it can be observed that the trends of the clusters follow the curve of the average normalized temporal signatures of 30 cities. The black curve shows that the afternoon/evening peaks appear stronger than morning peaks. In addition, trip frequency (or usage of e-scooters) is highest on Friday along with Saturday, and Sunday is typically associated with low usage. The patterns of each cluster are interpreted as follows.

- **Cluster** Br_1: The Br_1 contains five cities from Switzerland. Especially Basel and Zurich are more similar than other cities in terms of the temporal signatures, which is indicated by the dendrogram. In this cluster, the cities have three obvious peak points (including the lunch time peak point) on weekdays. Besides, the curves on weekend are close to the average normalized temporal signatures, while the probability curves from Monday to Friday are higher than the average normalized temporal signatures.
- **Cluster** Br_2: There are also five cities contained in the Br_2, including three Finnish cities (i.e., Helsinki, Turku, and Tampere), Stuttgart and Bern. Although Bern is contained in the cluster, its temporal signature is a bit different from that of the other

four cities on Sunday. In this cluster, the morning and lunch time peak points are not obvious compared with the average temporal signature, and the evening peak points move backwards, especially on Friday and Saturday.

- **Cluster** Br_3: Three Swedish (i.e., Gothenburg, Uppsala, and Stockholm) and four German (i.e., Munich, Berlin, Hamburg, and Cologne) cities are contained in the Br_3. The trends of the normalized temporal signatures follow the average normalized temporal signature. However, the trip volumes on Saturday and Sunday are higher than the average temporal signature. Stockholm is a special one whose morning peak point is more obvious than the average temporal signature.
- **Cluster** Br_4: The Br_4 only contains one city, namely Bergen, which has only one obvious peak point at 15:00 and 16:00 from Monday to Friday. Especially, Bergen obtains the highest upper boundary on Wednesday and Friday, which is not found in other clusters.
- **Cluster** Br_5: In the Br_5, we can find five German cities (i.e., Duesseldorf, Frankfurt, Hannover, Karlsruhe, and Muenster) and another three cities from Austria (Vienna), Norway (Oslo), and Sweden (Lund). The trends of the normalized temporal signatures are also consistent with the average normalized temporal signature, Yet, the trip volumes on Sunday of these cities are lower than the average normalized temporal signatures compared with Cluster Br_3.
- **Cluster** Br_6: Rome is also divided into a single cluster. As shown in 6, Rome does not have morning peaks on weekdays and obtains the highest upper boundary on Saturday and Sunday. Specifically, Rome has obvious lunch and evening peaks from Monday to Thursday. The lunch peak is indistinct on Friday and the curve on Friday also becomes more similar to Saturday. In addition, the curve on Sunday shows a higher probability and fluctuates at the period from 12:00 to 20:00. Note that, unlike Bergen, Rome has less e-scooter trips on the weekdays than on the weekends.
- **Cluster** Br_7: Milan, Paris and Lyon are contained in the Br_7. They have obvious morning and evening peaks and the upper boundaries of these cities on Saturday are lower than the average normalized temporal signatures.

Overall, these cities can be separated into several groups according to the hierarchical clustering method, and similar patterns can be found in the same group. There are no pairs of cities that are totally the same with each other. However, the cities in the same country are more likely to have a higher similarity. For example, the pairs of cities, such as Zurich and Basel, Muenster and Hannover, Uppsala and Gothenburg, Frankfurt and Duesseldorf, Munich and Berlin, Hamburg and Cologne, Turku and Helsinki, are grouped together directly with a lower variance. Although the cities in different countries can also be connected directly, such as Milan and Paris, Oslo and Karlsruhe, Stuttgart and Tampere, they have a longer connection distance than the above-mentioned pairs in the same country. In addition, the curve on Friday is more similar to that on Saturday in most cities. Although the trend on Saturday is similar to that on Sunday, the trip volume on Saturday is generally higher than that on Sunday.

5.2. Statistical analysis of e-scooter trips

In addressing **RQ2**, the statistical distributions of e-scooter trips across cities are explored in terms of trip distance and trip duration. The detailed distributions of trip distance and trip duration are illustrated in Figure S2 and Figure S3 in the supplementary material. The distributions of both indicators increase firstly and then decrease steadily, which follow right-skewed distribution for all the cities. Besides, it can be observed that the mean values are higher than median values in terms of trip distance and duration for each city, which also demonstrates the right-skewed distributions. By examining the statistics of distributions for each city, it is found that the median values of trip distance are within the range between 0.91 km (Zug) and 1.79 km (Paris), whereas the median values of trip duration are within the range of 5.67 min (Zug) and 13.77 min (Paris).

Moreover, the relationships between trip distance, the number of trips and trip duration are investigated, as shown in Fig. 7. Each sub-figure depicts how the median of trip distance (orange curve) and the number of trips (blue curve) during a given time interval change over the trip duration. Concretely, by dividing the trips into several groups according to trip duration (e.g., one-minute interval), the number of trips and the median of trip distance can be obtained for each group. Overall, the blue curves increase dramatically at the beginning, and are followed by decreasing tails for all e-scooter programs in these cities. This observation is consistent with that of the existing studies of micro-mobility (Li et al., 2020a; Zhu et al., 2020). The orange curves increase in a steep manner at the beginning and reach an upper boundary (named as the boundary distance) at a given time interval (named as the boundary minute) with the increase of trip duration.

In more detail, although the trip duration of e-scooters can reach up to more than one hour, the trips with duration less than one hour or even less than half an hour occupy a high proportion, as can be seen from Figure S3. Hence, the trip duration in Fig. 7 is limited to 60 min. By comparing the blue curves across these cities, it can be observed that the peaks are mainly concentrated on the range between three and five minutes in most cities. The finding is slightly different from that in the study by Zhu et al. (2020), which reports that it takes five to eight minutes to reach the peak of trip numbers in Singapore. An exceptional case is Paris where the trip number reaches the maximum until eight minutes with a trip distance at about 1.2 km, while the trip distance is less than one km during the peak interval for other cities.

Regarding the change of trip distances over trip duration, it can be further found that the boundary minute and boundary distance differ from each other in these cities. The boundary minute ranges from 12 to 32 min and the boundary distance is between 1.9 to 3.6 km. Compared with the cities with a larger service area (e.g., Berlin, Hamburg), the cities with a smaller service area (e.g., Bern, Basel, and Zug) have a smaller boundary distance and boundary duration. The calculated Pearson coefficients between the service area and the above-mentioned two variables are higher than 0.6, which are significant at the 0.01 level. Before reaching the boundary distance, a rough linear relationship between the trip distance and trip duration can be found in these cities, which is in line with the trend illustrated in the study by Zhu et al. (2020). In addition, for the trips approaching and after the boundary minute, they

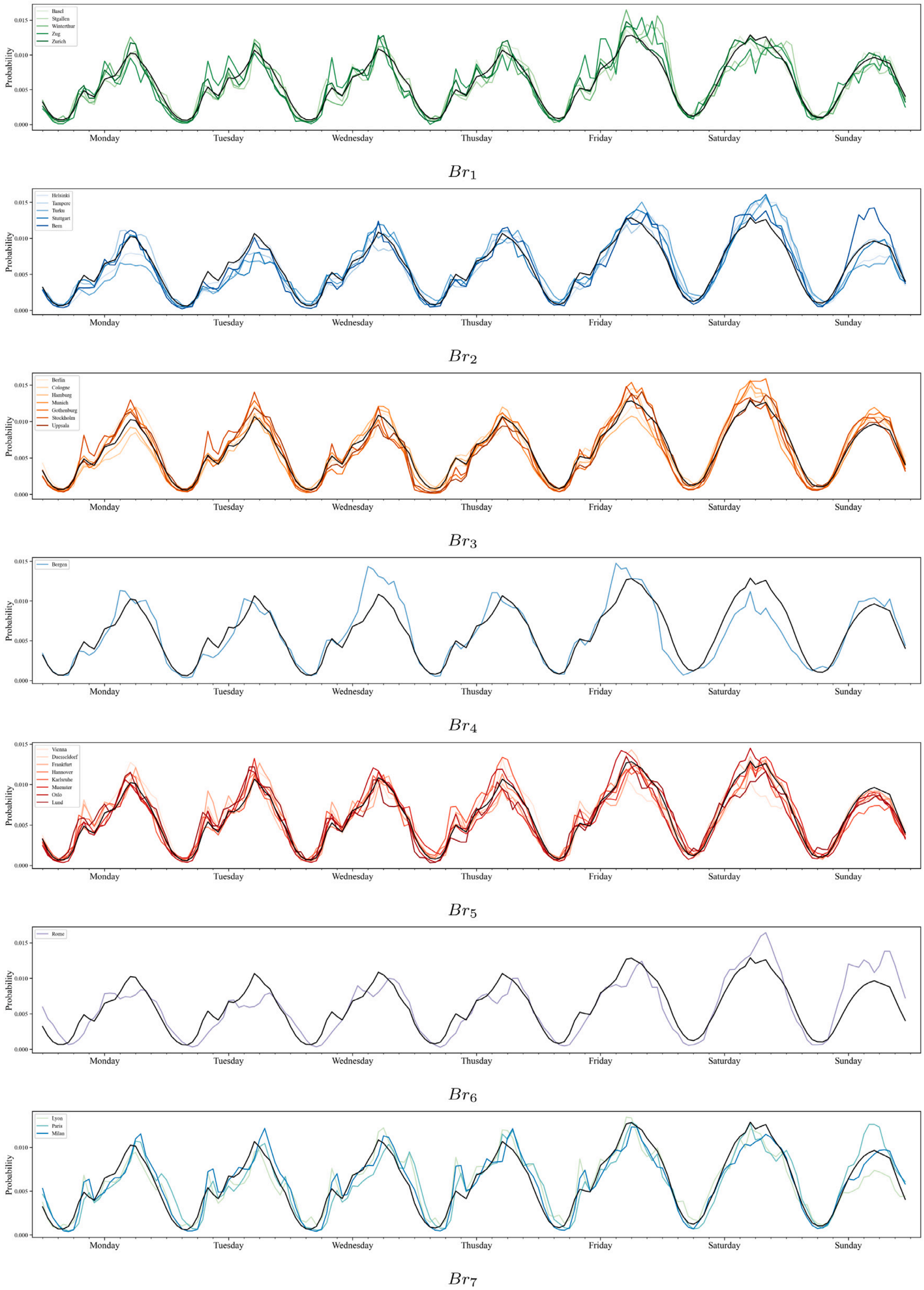


Fig. 6. Normalized temporal signatures aggregated on hourly during one week for the e-scooter services for each cluster. Probability in the Y-axis refers to the values of normalized temporal signatures.

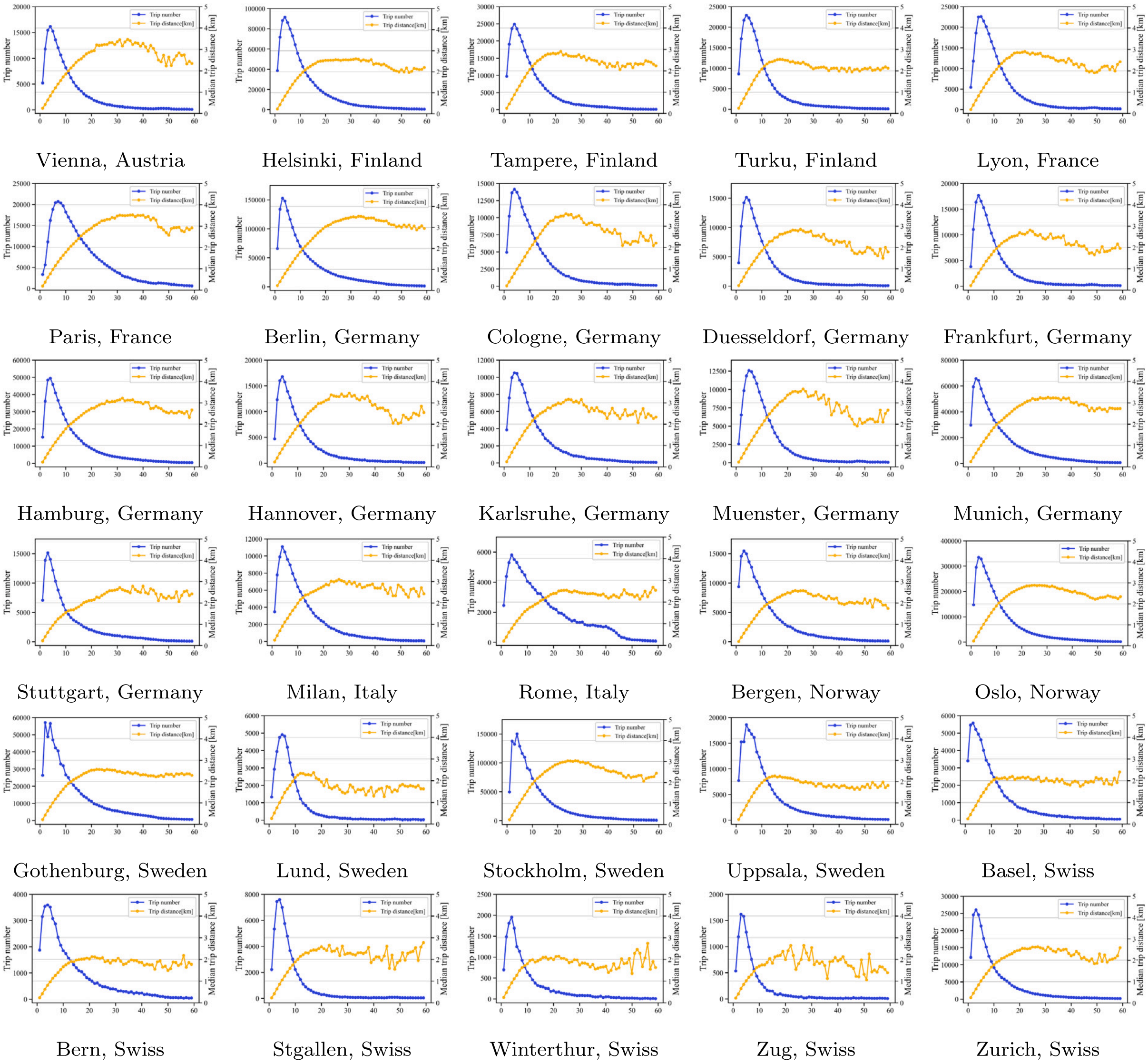


Fig. 7. The number of trips (left y-axis) and the median of trip distance (right y-axis) over trip duration with interval of one minute (x-axis) for these cities. Each sub-figure corresponds to one city. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

do not show an increase with the trip duration. The obvious example can be found in Stuttgart, Milan, Rome, Bergen, and Zurich. The curves before the boundary minute can be split into two parts according to their slopes, which represent two trip speeds. The trip speeds in the second part are lower that those in the first part. One possible explanation is that these trips with a longer trip duration are mainly for leisure activities, such as entertainment or tourism. The users prefer to take their time and enjoy their trips with a lower speed.

5.3. Comparison of utilization efficiency

In addressing **RQ3**, this section further compare the utilization efficiencies of e-scooter services in these cities, and the indicator TtB is adopted as the measurement to represent the utilization efficiency. For each city, the TtB value per e-scooter is calculated.

Fig. 8 shows the box plots of TtB for all the cities. In each row, the TtBs of all the e-scooters trips in a city are represented by a box plot. The median value and mean value are depicted by the blue lines and green triangles, respectively. The number on the right side of each box represents the corresponding median value. These cities from top to the bottom are sorted according to the median value of TtBs in each city. It is found that the median value of TtBs in each city is smaller than the mean value, which indicates that the distributions are right-skewed. To verify the conclusion, the detailed distributions of TtBs in each city are illustrated in Figure

Table 3
The Pearson coefficients between city factors and the median of TtBs.

City factors	Coef.	p
Population	0.093	0.619
City area	−0.031	0.869
Population density	0.161	0.386
E-scooter density	−0.143	0.444
Service area	−0.158	0.396
E-scooter volume per unit service area	−0.384	0.033**
E-scooter volume per person	−0.444	0.012**

**Means the coefficient is significant at 0.05 level.

S4 of supplementary material. Different from the distributions of trip distance and duration, the TtB shows a long tail distribution in each city. Although some e-scooters are used again after a short interval, most of them are utilized again after a long idle time.

The statistical value of TtB varies remarkably across these cities. For instance, the median values of TtB for these cities range from 0.75 h to 4.00 h. Interestingly, the cities with smaller median value of TtB are mainly located in the Northern Europe, while the cities with a bigger median value of TtB are concentrated in Germany, Italy, and Switzerland. Specifically, the median value of TtB in Gothenburg, Olso, Helsinki, and Tampere are less than one hour. Frankfurt, Milan, Zug, and Cologene are the four cities with longest Time to Booking in terms of their median values. However, an exceptional example can be found in Lund that has a median value of TtB more than 3 h, which could be attributed to the high popularity of bikes in Lund. Lund is a university town in the county of Skäne, Sweden, which has a strong cycling culture.[3] Most of the residents in Lund have their own bikes, which could limit the development of e-scooter sharing service. In addition, there is no obvious relationship between the TtB distribution and countries. The TtBs of different cities in a country may vary from each other. For example, the city in Switzerland that has the smallest TtBs is Bern, whose median value is 1.74 h. The e-scooters in Zug have to wait for a longer time period to be utilized again, whose median TtB (3.7 h) is more than twice higher than the value in Bern.

Moreover, we calculate the Pearson correlation coefficient to measure the relationship between the median of TtBs and the selected factors in a city (i.e., population, city area, and the number of e-scooter), as shown in Table 3. In these variables, only the density of e-scooters in terms of service area and the number of e-scooter per person have significant impact on the median of TtBs. The negative coefficients for the two variables denote that increasing the density of e-scooter and the number of e-scooter per person can decrease the time to booking, thereby improving the utilization efficiency. That results show that the median of TtBs has no significant linear relationship with the population, city area, the population and the density of e-scooters. The e-scooter density in terms of city area is not significant, whereas the e-scooter volume per unit service area has a significant correlation with the median of TtBs, which indicates that the calculated service area is a more suitable to delineate the utilization efficiency of e-scooters that city area. Besides, the number of e-scooters per person is also negatively and significantly related to the median of TtBs at the 0.05 level. One possible explanation is that the increasing of e-scooter volume can induce more demand on e-scooters and thus decrease the waiting time for the re-utilization of the same e-scooter.

5.4. Comparison of wasted electricity

In this section, we evaluate how much electricity of e-scooters is wasted during idle time in each city. The EWDIT values are calculated by Eq. (4) in each city, which are illustrated as a boxplot, as shown in Fig. 9. The boxplots are sorted from top to bottom according to the median of EWDIT values. Except for Cologne in Germany, whose mean value of EWDIT is higher than the median, most of cities have similar mean and median values of EWDIT. It indicates that these distributions are neither right-skewed nor left-skewed. The detailed distributions of EWDIT in these cities are shown in Figure S5 of supplementary material.

Although these cities present similar distribution in terms of EWDIT, the median of EWDIT in these cities spans from 15.07% to 55.26%. Intuitively, the longer when an e-scooter is parking, the more electricity will be wasted. We can speculate that there is a relationship between the idle time and the wasted electricity. To verify their association, the idle time and SOC change in all these cities are combined. As shown in Fig. 10, x-axis represents the change of SOC, which is the difference between the end SOC of the last trip and the start SOC of the current trip, and y-axis represents the idle time. Due to the SOC in our data are recorded as integer values, the changes of SOC are also integer values. Thus, the idle time spans are grouped by the SOC change. For each identical SOC change, the values of idle time are represented by the box plot. In addition, due to the integer type of SOC change, a small change smaller than one cannot be observed. Due to the values of SOC change smaller than 25% can occupy more than 99.4% of all the pair of data. Thus, these values are chosen to examine the relationship between idle time and wasted electricity. This is why the x-axis starts from zero and ends with 24%. The relationship between SOC change against TtB of all the data is shown in the upper-left corner of Fig. 10, where the curve of cumulative probability is shown.

Regarding the pattern that the change of SOC varies over idle time in Fig. 10, one possible explanation is that the wasted electricity for a battery can be influenced by many potential factors, such as the temperature of surrounding environment, the age of the battery, and so on. However, an obvious linear relationship between the SOC change and the median value of idle time can

[3] https://www.camcycle.org.uk/magazine/newsletter100/article10/.

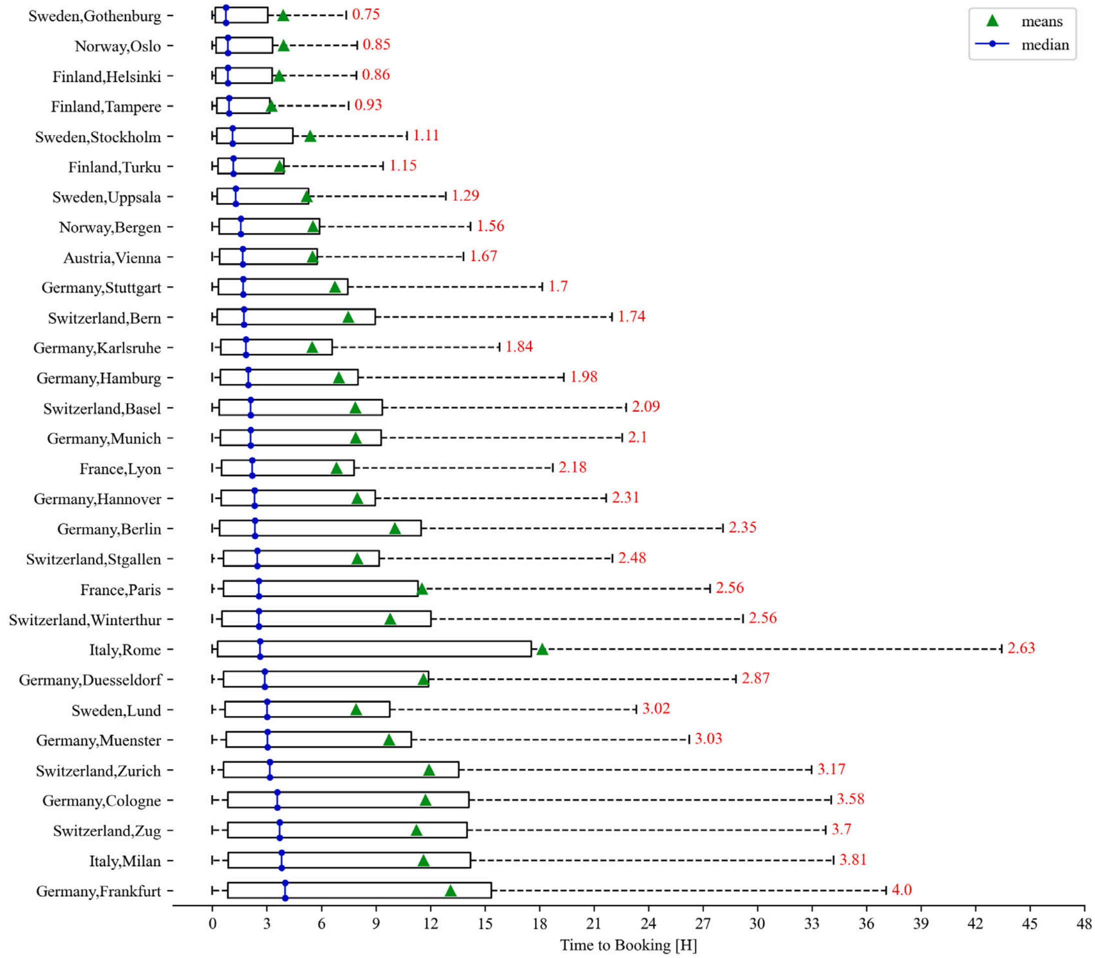


Fig. 8. The box plots of Time to Booking for all the cities. Each row represents a city. The blue line and the green triangle represent the median and mean of TtB. The red text is the median value. These cities are from top to bottom sorted by the median value of TtB.

be observed, especially for the pair of data where SOC change smaller than 25%. As shown by the red line in Fig. 10, the linear relationship with $R^2 = 0.94$ can be estimated between TtB and the median of duration, which demonstrates that a longer idle time will lead to a greater change of SOC.

6. Discussion and policy implications

6.1. Discussion

In the study, the research results can contribute to the knowledge of shared micro-mobility by modeling and characterizing e-scooter sharing mobility from four aspects, including temporal trip distribution, statistical trip distribution, utilization efficiency of e-scooters, and wasted electricity of e-scooters during idle time. Several key findings and policy implications are discussed in this section.

First, the temporal variations of e-scooter usage in 30 cities display similarities and differences in terms of the normalized average number of trips on an hourly basis over one week. According to such temporal variations, the 30 cities can be divided into seven clusters. An interesting finding is that only one significant peak is observed on weekdays in some cities, which indicates that e-scooter sharing may not be mainly used for commuting as bike-sharing. This phenomenon has been confirmed by previous studies when comparing bike-sharing and e-scooter sharing usage patterns (McKenzie, 2019; Reck et al., 2021). One potential reason for this finding is that e-scooters relying on the advantage of flexibility and convenience could satisfy the trips better for leisure, recreation, and sightseeing activities.

Second, as can be seen from the findings by examining the relationships between the number of trips, the median of trip distance and trip duration, the two relationships (i.e., blue curve and orange curve in Fig. 7) display the similar trends across the 30 cities regardless of the city size. The relationships are consistent with one prior study (Zhu et al., 2020). However, the peak locations of

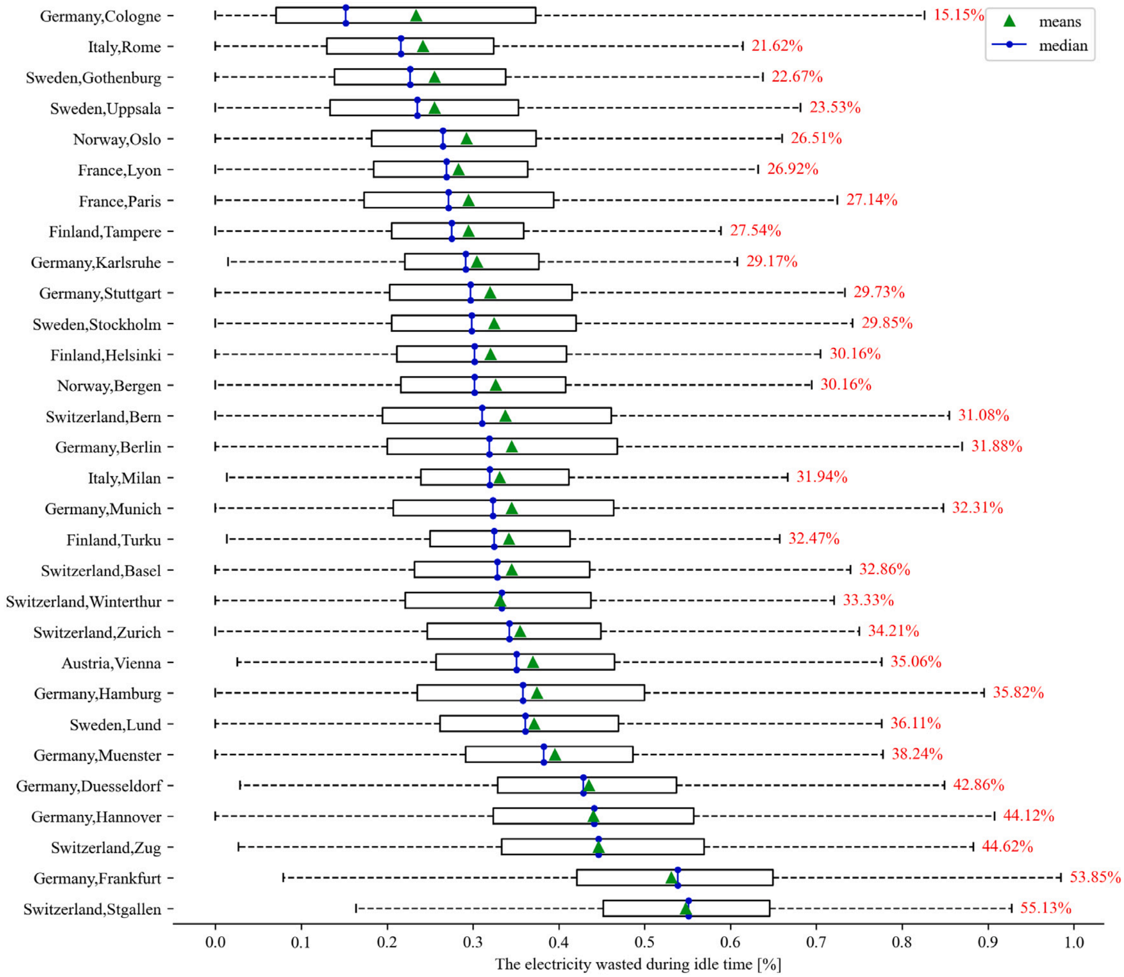


Fig. 9. The box plots of EWDIT for these cities. Each row represents a city. The blue line and the green triangle represent the median and mean of the EWDIT. The red text is the median value.

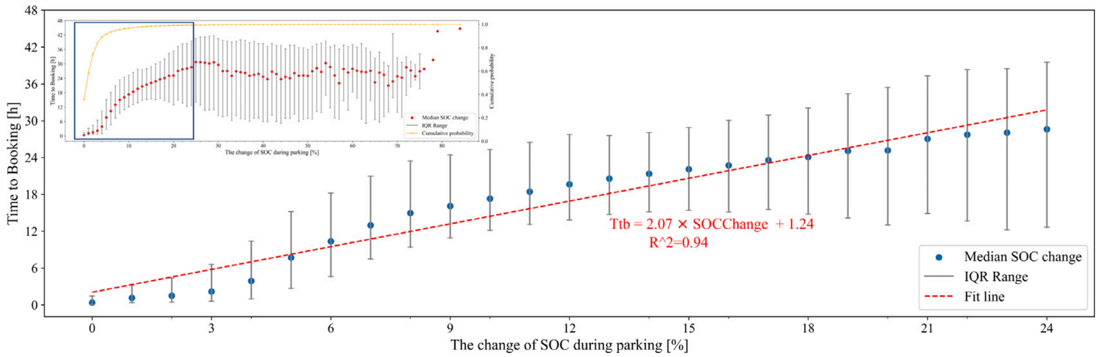


Fig. 10. The relationship between the change of SOC and idle time for all the trips in all the cities. The main figure describes the relationship between SOC change and TtB where the SOC changes are smaller than 25%. The sub-figure at the upper-left corner is the overview. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the blue curves are different from that of their research. This difference could be attributed to the size of study area/city, which has a remarkable influence on the trip distance distribution. For example, the average commuting distances in large and small cities can be different.

Third, the findings regarding the utilization efficiency of e-scooter sharing show that the utilization efficiency of shared e-scooters varies remarkably across these cities. It should be noted that this study introduces the Time to Booking to measure the usage efficiency of shared e-scooters. Compared with other indicators to measure the usage efficiency of e-scooter sharing like trip frequency (Caspi et al., 2020), the number of trips per e-scooter (Ciociola et al., 2020), Time to Booking is capable of measuring the utilization efficiency of micro-mobility services in an area from both supply and demand perspective (Li et al., 2020b). In terms of the number of trips per e-scooter, it measures the usage of e-scooter from the perspective of users and is partly influenced by ride duration and users' behavior. For example, given two e-scooters A and B during a certain period, it is assumed that e-scooter A was ridden in a long time during one trip, while e-scooter B was ridden for several short trips during the same period. It is evident that A has lower usage frequency even if it was used more efficiently during this period. Hence, Time to Booking is superior in measuring e-scooter sharing utilization frequency to some extent.

Finally, there is no research to quantify how much electricity of e-scooters is wasted during idle time. The results demonstrate that, on average, about one third (32.9%) of the electricity is wasted when an e-scooter is idle. This highlights that a large amount of e-scooter battery energy is wasted at that time and further work is required to minimize energy consumption when the e-scooters are not in use. Besides, it is also found that the wasted electricity during idle time displays a high correlation with the Time to Booking. Therefore, to reduce the wasted electricity of e-scooters, it is important to improve the utilization efficiency of e-scooter sharing services.

6.2. Policy implications

The research results can provide practical implications to improve the e-scooter sharing services. First, when urban planners attempt to implement e-scooter sharing services in a new city, the lessons learned from the cities where the e-scooter sharing services have been running can be beneficial for the planning. For instance, the temporal trip distributions of e-scooter sharing in many cities do not show obvious morning and evening peaks on weekdays unlike the case of bike-sharing. It implies that e-scooter sharing may not play a significant role of supporting commuting travels, which can aid urban planners and transport practitioners better understanding the role of e-scooter sharing and design the scheme according to the requirements before introducing it to a city.

Second, the findings indicate that the utilization efficiency of the current e-scooter sharing services has a large potential for further improvement. To obtain higher utilization efficiency, the newly implemented e-scooter sharing systems should provide appropriate amount of e-scooters, so that the number of e-scooters can match well with the population size and the served areas. If the amount of provided e-scooters exceeds extremely the required number, it will cause the waste of resources and urban space. However, if the amount of provided e-scooters is far less than the real demand, which implies that the e-scooters are distributed sparsely in urban space. Since the scattered e-scooters are not able to satisfy user's travel demand, which may influence users' long-term usage, thereby impacting the utilization efficiency of the e-scooters in the future. Hence, it is important for urban planners and policy makers to design and implement more appropriate scheme on e-scooter sharing service by considering the characteristics of city, such as city size, service area, urban morphology, population size, and so on.

Finally, the findings provide evidence that a substantial proportion of the electricity stored in e-scooter batteries (about one third) is wasted when they are idle. Since e-scooters are electricity driven mode, the results suggest that the related policies or schemes require be designed to decrease their wasted electricity during idle time. For instance, it is advisable to strengthen the dynamic rebalancing mechanisms, which can decrease the idle time between two consecutive trips for each e-scooter by facilitating passengers to find an available e-scooter within less time, thereby improving the performance of the e-scooter sharing system. Another solution could be designing appropriate parking areas for e-scooters to avoid the circumstances that users park e-scooters in remote and sparsely populated places. It can also reduce the wasted electricity of e-scooters by improving their utilization efficiency. Besides improving the utilization efficiency to reduce the idle time of e-scooters, it also suggests that operators and producers of e-scooters should attempt to optimize the power-consuming devices of e-scooter. For instance, the positioning method of e-scooters can be improved to decrease the wasted electricity due to the equipped accessory devices (e.g., GPS). Since the GPS device keeps positioning the locations of e-scooter that do not change during idle time, this process can be further optimized. One solution is that the last position of the e-scooter could be uploaded by user through his/her mobile phone and recorded by the operator. Then, the recorded position will be updated dynamically by users. In this situation, it might be not necessary to position the location of e-scooter via GPS all the time.

7. Conclusion

As an convenient and emerging transport mode of urban mobility services, e-scooter sharing services have attracted much attention to urban planners and urban analytic researches. Although a series of studies has analyzed the e-scooter sharing mobility patterns, which are still focused on one or few cities. Little attention has been paid to comprehensively and systematically investigating similarity and difference of e-scooter sharing mobility patterns by extracting evidence from multiple cities in different countries. In this work, a comparative study is conducted to reveal the similarity and difference in four aspects by collecting and analyzing vehicle availability data from 30 European cities.

First, the temporal variations of e-scooters trips in terms of the averaged number of trips on an hourly basis over one week are analyzed and compared to uncover the similarity and difference of e-scooter sharing mobility patterns in the selected cities. These cities can be divided into seven clusters according to their temporal variations of trips. Second, the statistical distribution on e-scooter trips is explored, which suggests that both trip distance and duration follow right-skewed distribution for all the cities. The statistics like the medians of trip distance and duration, however, vary across the cities, which are within the range between 0.91 km (Zug) and 1.79 km (Paris), and the range of 5.67 min (Zug) and 13.77 min (Paris) respectively. Third, the utilization efficiency of e-scooter sharing mobility services are measured in terms of Time to Booking for each city. It is observed that the distribution of TtB in each city follows a long tail distribution. However, the TtB values vary across the cities. For example, the cities in the Northern Europe are more likely to have higher utilization efficiency on e-scooter sharing mobility services. Finally, we quantify how much electricity of e-scooters are wasted during idle time in each city. The results show that the median of EWDIT in these cities spans from 15.07% to 55.26%. Overall, the similarity and difference co-exist among e-scooter sharing services in different countries in terms of their temporal patterns, statistical distributions, utilization efficiency, and wasted energy during idle time.

It is worth noting that this study still suffers several limitations. First, due to the data limitation, only the cities in Europe are analyzed and compared in this study. Currently, near two hundred cities in Europe and USA have implemented e-scooter sharing services. They have many differences in terms of culture, geography, economy, etc., which may cause more variances than the selected cities of this study. Second, these data were collected starting from March, 2021 and these cities are still within the COVID-19 period. The human travel behaviors may be influenced by the pandemic and lockdown policies according to the study (Li et al., 2021b). Even though these cities were recovering from the COVID-19 pandemic during the period, the potential impacts on travel behavior are still unknown. It implies that the obtained results and conclusions may not be able to completely represent the e-scooter sharing mobility patterns in the general situation. Third, even if the two micro-mobility operators where we collected the data occupy high market shares of shared e-scooters in those cities, it would be meaningful to also take into account the data from other operators. Last but not least, although we analyze the potential explanations of the similarity and difference of e-scooter sharing mobility patterns in these cities, most of them are qualitatively analyzed. The impact of more explanatory factors in social, cultural, infrastructural dimensions can be further explored to obtain a more complete picture.

Acknowledgments

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.trd.2022.103229.

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