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How did micro-mobility change in response to COVID-19 pandemic? A case study based on spatial-temporal-semantic analytics

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ARTICLE INFO
Keywords:
COVID-19
Micro-mobility
Docked and Dockless bike-sharing
Spatio-temporal patterns
Trip purpose

ABSTRACT
Cities worldwide adopted lockdown policies in response to the outbreak of coronavirus disease 2019 (COVID-19), significantly influencing people’s travel behavior. In particular, micro-mobility, an emerging mode of urban transport, is profoundly shaped by this crisis. However, there is limited research devoted to understanding the rapidly evolving trip patterns of micro-mobility in response to COVID-19. To fill this gap, we analyze the changes in micro-mobility usage before and during the lockdown period exploiting high-resolution micro-mobility trip data collected in Zurich, Switzerland. Specifically, docked bike, docked e-bike, and dockless e-bike are evaluated and compared from the perspective of space, time and semantics. First, the spatial and temporal analysis results uncover that the number of trips decreased remarkably during the lockdown period. The striking difference between the normal and lockdown period is the decline in the peak hours of workdays. Second, the origin-destination flows are used to construct spatially embedded networks. The results suggest that the origin-destination pairs remain similar during the lockdown period, while the numbers of trips between each origin-destination pair is reduced due to COVID-19 pandemic. Finally, the semantic analysis is conducted to uncover the changes in trip purpose. It is revealed that the proportions of Home, Park, and Grocery activities increase, while the proportions of Leisure and Shopping activities decrease during the lockdown period. The above results can help planners and policymakers better make evidence-based policies regarding micro-mobility in the post-pandemic society.

1. Introduction

The pandemic outbreak of novel coronavirus disease 2019 (COVID-19) has caused radical social changes world-wide, and posed a large threat to health, life and livelihood of the populations (Gatto et al., 2020; Kraemer et al., 2020; Oliver et al., 2020). As of October 1, 2020, there had been more than 34,048,240 confirmed cases and 1,015,429 deaths around the world. Due to the pandemic, Italy applied a national lockdown in response to the spread of COVID-19 on March 9, 2020 after China, and was also the first European country to implement a lockdown (Bonaccorsi et al., 2020). As of October 1, 2020, there had been more than 34,048,240 confirmed cases and 1,015,429 deaths around the world. Due to the pandemic, Italy applied a national lockdown in response to the spread of COVID-19 on March 9, 2020 after China, and was also the first European country to implement a lockdown (Bonaccorsi et al., 2020). Following Italy and China, some other countries also conducted national lockdowns successively. For example, Swiss government announced that schools and most shops were closed nationwide from 16 March, 2020. During the lockdown period, almost all the public facilities like schools, shops are closed, and all public events are banned. Also, people are requested to work from home and encouraged to stay at home to reduce unnecessary trips (Engle, Stromme, & Zhou, 2020). It is evident that COVID-19 pandemic had a significant impact on human mobility and urban transportation.

As the environmentally friendly transport modes, shared micro-mobility services (e.g., docked and dockless bike-sharing, e-scooter sharing) are playing a crucial role in human daily travel. In such a situation, micro-mobility was undoubtedly influenced by the epidemic of COVID-19. On the one hand, to keep social distancing, an increasing number of people chose to stay at home to minimize going out for the dispensable activities during the pandemic period, which implies that the number of trips taken by micro-mobility would decrease intuitively. On the other hand, people’s intention might have increased to substitute public transportation with micro-mobility transportation modes for the necessary short- or medium-distance trips to reduce the risk of getting...
infected in public transportation. Therefore, it would be necessary to explore how micro-mobility changes in response to COVID-19 pandemic, which is beneficial for understanding micro-mobility patterns and enhancing the effective scheduling of bikes during pandemic period.

In recent years, shared micro-mobility services have attracted considerable attention in academic and industrial fields, which have proved to be able to facilitate alleviating traffic congestion and transport-related emissions (Li, Gao, Zhao, Qu, & Axhausen, 2021; McKenzie, 2020; Milakis, Gebhardt, Ehebrecht, & Lenz, 2020; Wang & Zhou, 2017; Zhang & Mi, 2018). Especially, with the rapid development of mobile computing and payment, micro-mobility services have been realized as effective alternatives to short- and medium-distance trips by public and private car transportation. The services allow users to locate and unlock a bike/e-scooter almost everywhere through smartphones and park it after completing the trip. Although micro-mobility services bring convenience for people’s travel, several issues are still facing the city and urban transportation. In particular, considering the various types of micro-mobility services, including docked and dockless bike, electric bike (e-bike), little is known about the similarity and difference of micro-mobility patterns for different types of services, especially how these micro-mobility patterns change in response to COVID-19 pandemic.

The goal of this study is to investigate the changes of micro-mobility usage before and during the COVID-19 pandemic period by conducting a case study in Zurich, Switzerland. Exploiting high-resolution trip data of docked bikes, docked e-bikes and dockless e-bikes, we conduct spatial, temporal, and semantic analytics. We divide the dataset into two parts based on the lockdown date, namely the normal period (NP) and lockdown period (LD). First, the spatial and temporal changes of trips for the three types of micro-mobility services are examined. Second, spatial network analysis is conducted to explore the micro-mobility patterns from the perspective of spatial interaction. Third, semantic analytics are implemented to uncover how different types of activities vary before and during the pandemic periods.

The remainder of this paper is organized as follows. Section 2 reviews human mobility in response to COVID-19, micro-mobility patterns, and trip purposes imputation. Section 3 briefly describes the data and the data preprocessing. Section 4 introduces the methodology of this paper. Section 5 presents the results of micro-mobility changes during Normal and Lockdown periods, followed by discussion of the results in Section 6. Finally, we highlight our conclusions in Section 7.

2. Literature review

2.1. Human mobility in response to COVID-19

Since the outbreak of COVID-19, several studies have been conducted to investigate how human mobility reacts to the epidemic. For instance, Kraemer et al. (2020) examined the effect of human mobility on the COVID-19 epidemic in China using the mobility data from Wuhan and the detailed case data including travel history. The work by Galeazzi et al. (2020) performed a massive data analysis to explore how human mobility patterns changed dramatically during the pandemic period. Molloy et al. (2020) examined the mobility patterns before and after the start of the pandemic in Switzerland using the participants’ GPS trajectory data from the MOBIS-COVID-19 tracking study. The drastic reduction in mobility after the implementation of lockdown measures was observed.

In addition, Google community mobility reports are also used to analyze mobility dynamics during the pandemic period, which plot movement trends over time across different types of places, such as residential, workplaces, public transport, retail, supermarkets, parks, and pharmacies. The study from Saha, Barman, and Chouhan (2020) examined the impact of lockdown for COVID-19 on community mobility in India using the Google community mobility reports. It was found that retail and recreation, grocery and pharmacy, visits to parks, transit stations, and workplaces mobility decreased dramatically, while residential mobility increased during the lockdown. Hakim et al. (2021) analyzed the community mobility and COVID-19 case counts using Google community mobility reports in Australia, Japan, Hong Kong, and Singapore. The results showed that the community mobility decreased in Australia, Japan and Singapore, while Hong Kong had little change during the period.

2.2. Understanding micro-mobility patterns

Many studies have explored and analyzed human micro-mobility patterns using various micro-mobility data. Most of these studies are concentrated on understanding bike-sharing mobility patterns, which consist of docked and dockless bike-sharing systems. For instance, Wergin and Buehler (2017) examined the travel behaviors of two types of bike-sharing users (i.e., short- and long-term) by analyzing the trips of bikes between docking stations. Xu et al. (2019) uncovered the temporal variations of bicycle usages at various locations in Singapore using an eigendecomposition approach, which indicated different space-time characteristics of cycling activities on weekdays and weekends. Yang, Heppenstall, Turner, and Comber (2019) investigated the changes of travel behaviors by analyzing bike-sharing during a period when a new metro line came into operation in Nanchang, China. The results showed how the spatiotemporal patterns of bike travel behavior changed over the period. A comparative study was conducted to examine the difference in travel characteristics between docked and dockless bike-sharing systems. It was found that shorter average travel distance and travel time are achieved for dockless bike-sharing systems, while higher use frequency and hourly usage volume are obtained in contrast with docked bike-sharing systems (Ma, Yuan, Oort, Ji, & Hoogendoorn, 2019). McKenzie (2019) identified the differences and similarities between dockless e-scooters and bike-sharing services by showing the spatial and temporal activity patterns of the two platforms. There are essential differences between the two services. Li, Zhao, Huang, Gao, and Axhausen (2020) explored dockless bike-sharing utilization pattern and its explanatory factors by implementing an empirical study of GPS bike origin-destination data in Shanghai. McKenzie (2020) conducted a comparison study to explore the spatial and temporal similarities and differences by comparing the e-scooter and e-bike from different micro-mobility companies. Zhu, Zhang, Kondor, Santi, and Ratti (2020) investigated the impact of the fleet size, operational regulations (dockless versus docking), and weather conditions on the usage patterns between bike-sharing and e-scooter sharing by conducting a comparative analysis, thereby further deepening our understanding of their spatiotemporal heterogeneity. Reck, Haitain, Guidon, and Axhausen (2021)
conducted an empirical study on shared micro-mobility usage, competition and mode choice using data from Zurich, Switzerland. A generally applicable data processing framework is proposed to examine the impact of data processing on deriving micro-mobility patterns from vehicle availability data, which is applied to a case study dataset from Zurich (Zhao, Haitao, Li, & Mansourian, 2021).

### 2.3. Predicting trip purpose on micro-mobility

As one of the crucial characteristics of human mobility, trip purposes are significant for understanding human travel behavior and estimating travel demands. A large number of studies have been conducted to predict trip purposes using various GPS-based human mobility datasets. For instance, Deng and Ji (2010) presented a machine learning approach to impute trip purposes from GPS track data by combining with other relevant data sources like land use. Lee and Hickman (2014) developed an approach to derive passengers’ trip purposes from the farecard transaction data, which can contribute to the development of heuristic rules for trip purpose inference. The study from Alexander, Jiang, Murga, and Gonzalez (2015) exploited mobile phone data to infer activity types based on observation frequency, day of week, and time of day, etc. Li and Axhausen (2018) proposed a framework to infer trip purposes from GPS-based taxi trajectory data by considering the location and time of drop-off points as well as the trajectory form. The work by Zhao, Liu, Kwan, and Shi (2020) proposed a method to identify cabdrivers’ dining activities from GPS taxi trajectory data based on the support vector machine (SVM) algorithm. Overall, rule-based methods and machine learning algorithms are still the mainstream of trip purpose inference.

With the booming of bike-sharing systems, several studies were implemented to predict trip purposes from bike-sharing movement data. For instance, Bao, Xu, Liu, and Wang (2017) investigated bike-sharing travel patterns and trip purposes by conducting the Latent Dirichlet Allocation (LDA) analysis from bike-sharing smart card data and online point of interests (POIs) data. Li, Huang, and Axhausen (2020) applied a Dirichlet multinomial regression topic model (DMR model) to infer trip purposes from bike trajectories by considering arrival time and drop-off location. Xing, Wang, and Lu (2020) investigated the trip purposes of bike-sharing users using the bike-sharing data and online POIs. Specifically, the spatial attractiveness of each POI category within the walkable distance around origin or destination is calculated. Kou, Wang, Chiu, and Cai (2020) inferred trip purpose by comparing the trip speed to the average speed of all trips in the city, thereby quantifying greenhouse gas emissions reduction from bike share systems. Considering above, little attention has been paid to explore and understand micro-mobility patterns from the perspective of trip purpose, especially during the COVID-19 pandemic.

### 3. Data description and preprocessing

#### 3.1. Micro-mobility trip data

Zurich is one of the major cities and economic centers in Switzerland, with 434,000 inhabitants. Fig. 1 shows the study area, which is divided into 31 sub-regions according to postal codes (PLZ) in Switzerland. The area contains Zurich city (24 PLZs) and surrounding Postal codes zones (7 PLZs).

We collected data of three types of micro-mobility services from two operators. Operator1 is the most established bike sharing services in Switzerland, offering docked bikes and docked e-bikes. The study area contains 153 docking stations, as shown in Fig. 1. Operator2 offers a dockless e-bike service. Compared with the e-bikes from Operator1, the e-bikes of Operator2 can travel at a higher speed (up to 45 km/h). As most e-scooter companies stopped their services after March 15, 2020 (the date of lockdown in Switzerland), e-scooter service is not taken into consideration in this research.

The micro-mobility trip data is collected from the two micro-mobility operators. Each trip contains ID, start time, start location, end time, end location, trip duration, and trip distance. Although these trip data belongs to different types of micro-mobility services, the duration of the trips are between two minutes and one hour. A summary of the data description is listed in Table 1. The data span from February 15 to April 14, 2020, covering the normal period (NP: February 15 to March 14, 2020) and part of the lockdown period (LD: March 15 to April 14, 2020) according to the lockdown date of Switzerland. Fig. 2 plots the number of trips for each type of service per day during the two periods. The dashed lines represent the average number of trips during the two periods for each type of micro-mobility service respectively. It can be observed that the average number of trips decreased remarkably during the Lockdown period compared with that of the Normal period, which is in agreement with the conclusions from previous studies (Molloy et al., 2020) using GPS tracking data.

#### 3.2. Point of interest

The Point of interest (POI) dataset was extracted from Open-StreetMap, containing 41,322 records. Each POI record has several attributes, including ID, name, type, and location (longitude and latitude). Since business hours are not available in the POI dataset, we assign business hours to each type of POI based on their typical business hours in the study area. In this study, we further divide these POIs into eight common categories, including Home, Work (e.g. companies, government offices), Transport (e.g. tram, bus, and train stations), Education (e.g. kindergarten, primary school, or university), Leisure (e.g. theater), Shopping (e.g. shopping malls, clothing shops), Grocery (the shops related to daily life, such as supermarket), Park (mainly refer to facilities providing outdoor activities). Table 2 displays the eight POI categories and their assumed business hours.

#### 3.3. GPS Survey data

GPS survey data were collected by the MOBIS study in Switzerland (Molloy et al., 2020). MOBIS study was implemented by the Institute for Transport Planning and Systems at ETH Zurich and the WWZ of the University of Basel from September 2019 to January 2020. The survey invited 3700 participants from German and French speaking regions in Switzerland randomly. Each of them was asked to install the GPS Logger and Travel Diary App ‘Catch-My-Day’, developed by MotionTag. The App can record the participants’ trajectories automatically and participants were asked to validate their activity information for their stay points and trips. A stay point is a location where a user stayed beyond a certain time period. Here, we extract these stay points within the study area, containing 92,539 records. Each record has start time, end time, activity type, and location. These records consist of ten kinds of activities, which are listed in Table 3.

### 4. Methodology

In this study, we conduct the analytics on how micro-mobility services change from three aspects, including spatial-temporal analysis, spatial network analysis, and semantic analysis. The spatial and temporal analysis focuses on the overall micro-mobility patterns in time and space. The spatial network analysis aims to explore how people move between spatial units from the perspective of interaction. Semantic analysis uncovers micro-mobility patterns by predicting trip purposes and dividing the trips into different categories based on purpose. Spatial network analysis and semantic analysis based on trip purposes are introduced in this section.
4.1. Spatial network analysis

With the boom of human mobility data and development of network science, spatial network analysis has been commonly used to understand urban interactions by analyzing human or vehicle movement within different urban areas (Liu, Gong, Gong, & Liu, 2015; Zhao, Liu, Shi, et al., 2020; Zhong, Arisona, Huang, Batty, & Schmitt, 2014). It provides insights into urban phenomena and regularities generated by human mobility. In this study, each trip contains the origin and destination. The interaction flows between geographic units can be represented as an origin-destination matrix (OD matrix). Based on the OD matrix, a directed weighted graph \( G = (N, E, W) \) can be constructed, where \( N \), \( E \), \( W \) represents the node, edge, and weight of edge. A node \( N_i \) denotes a sub-region, whose centroid coordinate \((x_i, y_i)\) is regarded as the spatial location of the node. If there is a micro-mobility trip between two nodes \((N_i, N_j)\), an edge \( E_{ij} \) can be generated. Furthermore, the weight \( W_{ij} \) of each edge \( E_{ij} \) is defined as the number of trips departing from node \( N_i \) and arriving at node \( N_j \).

Considering the two periods (i.e. the normal period and the lockdown period) and three types of micro-mobility services, we construct six networks for the three types of micro-mobility services during each period. After constructing these networks, the following indicators are employed to examine the micro-mobility patterns from the perspective of network and interaction.

- **Degree** of a node is defined as the number of edges connected to it. In this study, degree is divided into out-degree and in-degree according to the trip direction between each pair of nodes.
- **Strength** of a node refers to the sum of the weights of all edges connected to it, which includes in-strength and out-strength likewise.
- **Average degree** is calculated as the average value of degree for all nodes in the graph, reflecting the connectivity of the whole graph.
- **Average strength** is calculated as the average value of strength for all nodes in the graph.
- **Graph density** measures the sparseness and denseness of edges in a graph.

These indicators are beneficial to exploring and understanding the characteristics of the constructed networks. By comparing these properties, we can further detect how the micro-mobility behavior change before and during COVID-19 pandemic from the perspective of spatial interaction.

### Table 1

| Operator   | Type          | Range of period | The number of trips |
|------------|---------------|-----------------|---------------------|
| Operator 1 | Docked bike   | 2020-02-15 - 2020-04-14 | 41,954 - 26,746 |
| Operator 1 | Docked e-bike | 2020-02-15 - 2020-04-14 | 13,963 - 8,985 |
| Operator 2 | Dockless e-bike | 2020-02-15 - 2020-04-06 | 7,259 - 3,079 |

Fig. 1. Study area.
4.2. Semantic analysis based on trip purpose

Most existing studies on exploring micro-mobility patterns are mainly concentrated on spatial and temporal dimensions, which pay little attention on underlying semantic context. Actually, what people do at places, as the root of human mobility patterns, also deserve to be studied. Hence, semantic analysis based on trip purpose is conducted to further understand how micro-mobility changes in response to COVID-19 pandemic. Micro-mobility OD data are passively collected without information on activity types at origin and destination. This information is essential to understand how human travel activities by micro-mobility services change during the pandemic period. The core of this section is to predict purposes for the trips of the three types of micro-mobility services. In this study, we impute the purposes of both origin and destination for each trip, namely Origin activity and Destination activity.

In this study, we utilize micro-mobility data from two types of sharing systems, i.e., dockless sharing system and docked sharing system. Compared with a docked sharing system that passengers have to pick up and drop off bike or e-bike at specific stations, passengers can pick up and drop off them almost anywhere for a dockless sharing system. Thus, we need to infer their activities independently. A framework is developed to impute the trip purposes for both docked and dockless bikes based on previous trip purpose prediction methods (Gong, Liu, Wu, & Liu, 2015; Zhao, Kwan, & Qin, 2017), as illustrated in Fig. 3. The framework comprises four steps, which are introduced in the subsections.

4.2.1. Identifying candidate POI

Two rules are applied to identify candidate POI for each origin or destination. First, the candidate POI should be open at the departure or arrival time. The business hours of POIs are defined based on prior

Table 2
POI categories and business hours.

| Activity   | POI categories | Business hours | Closing days |
|------------|----------------|----------------|--------------|
| Home       | Apartment      | [0:00, 24:00)  | No           |
|            | House          | (0:00, 24:00)  | No           |
| Work       | Office         | (7:00, 19:00)  | Sunday       |
| Transport  | Train station  | (0:00, 24:00)  | No           |
| Education  | University     | (0:00, 24:00)  | No           |
|            | Primary School | (7:00, 19:00)  | Weekend      |
| Leisure    | Art Center     | (8:00, 22:00)  | Sunday       |
|            | Museum         | (8:00, 19:00)  | Monday       |
|            | Restaurant     | (9:00, 21:00)  | Sunday       |
|            | Bar            | (0:00, 24:00)  | Sunday       |
|            | Zoo            | (9:00, 17:00)  | No           |
| Shopping   | Mall           | (9:00, 21:00)  | Sunday       |
|            | Clothing shop  | (7:00, 20:00)  | Sunday       |
| Grocery    | Pharmacy       | (7:00, 18:00)  | Sunday       |
|            | Grocery store  | (7:00, 21:00)  | No           |
| Park       | Dog Park       | (0:00, 24:00)  | No           |
|            | Park           | (0:00, 24:00)  | No           |

Table 3
The activity type in GPS tracking data.

| Name        | Count | Share (%) |
|-------------|-------|-----------|
| Home        | 28,000| 30.26     |
| Work        | 24,737| 26.73     |
| Leisure     | 14,135| 15.27     |
| Shopping    | 6575  | 7.11      |
| Errand      | 5579  | 6.03      |
| Assistance  | 3118  | 3.37      |
| Study       | 2644  | 2.86      |
| Home office | 271   | 0.29      |
| Co-working  | 240   | 0.26      |

Fig. 2. Number of trips per day for the three types of micro-mobility services during the two periods.
knowledge, as displayed in Table 2. Second, candidate POIs are within the influence area of pick-up or drop-off points. The influence area should be defined for docked and dockless services respectively due to their operation differences.

For dockless service, the candidate POI should be within the walking distance threshold (δ) from the pick-up or drop-off points, which is defined based on previous studies (Gong et al., 2015; Li, Huang, et al., 2020). Fig. 4 shows the percentage of trips that contain at least one candidate POI within a δ range from 10 m to 200 m. The increase for e-bike become smaller after around 50 m.

For a docked sharing system, the bike or e-bike can only be stopped at specific docking stations. It means that the real origin or destination could be far away from docking stations. For docked sharing system, we identify candidate POI based on the voronoi diagram, maximum walking distance (MWD), and minimum service area. By using voronoi diagram, each POI is assigned to the nearest docking station. However, for subrub where the docking station is in a low density, a POI could be very far away from the nearest docking station. Thus, we only consider the POI within a maximum walking distance (MWD), which is set as 50 m in this study. In addition, for the urban center where docking stations could be close, it is possible for a passenger to select a farther docking station, especially when no bikes or e-bikes are available in the nearest docking station. The POI within the minimum service area will be considered. A minimum service area is defined as a circle centered at a docking station. The diameter is the average distance of pairs of two nearest docking stations. 313 m is calculated from these docking stations.

A. Li et al.

| Data | Micro-mobility trip data | POI | Docking station | MOBIS survey data |
|------|--------------------------|-----|-----------------|-------------------|

**Candidate POI selection**

| Docked services | Dockless services |
|-----------------|-------------------|
| • Micro-mobility trip data | • Voronoi diagram |
| • Business hour | • Minimum service area |
|                  | • Maximum walking distance |
|                  | • Business hour |

**Identifying candidate POI**

| Temporal attractiveness | Spatial attractiveness |
|-------------------------|------------------------|
| • Origin activity probability | • Distance decay |
| • Destination activity probability | • POI attractiveness |

**Calculating POI visit probability**

- Bayes rules to calculate visit probability for each POI

**Determining the activity type of origin and destination**

- The activity of origin or destination is represented by the probability of each activity

**Fig. 3. Flowchart of trip purpose imputation**

For each type of activity, the visitation probability is shown in Fig. 5. The whole week is divided into 48 slots. The first 24 slots are the probabilities of workdays, and the last 24 slots are the visitation probabilities of weekends. All the MOBIS activities are assigned to the 48 slots based on their start time and end time for all the activities. The frequency of each slot is the average of the numbers of activities. Due to the mismatch between activities in the MOBIS data and POI data, we use the temporal attractiveness of Shopping and Leisure in the MOBIS data as Grocery and Park in POI data, respectively.

Based on Fig. 5, we can see that the visiting probability of the start time and end time varies significantly for most activities. For example, the end time of home activity peaks at around 7:00 AM during the workday, while the start time of home activity peaks at around 6:00 PM during the workday. Work activity displays a similar pattern during workday. The peaks for the start time and end time differ remarkably during workdays. These conclusions show that it is necessary to treat the origin activity and destination activity differently when imputing trip purpose.

**4.2.2. Spatial and temporal attractiveness**

Spatial attractiveness contains two factors, including the attractiveness of each candidate POI and the distance between a POI and given pick-up or drop-off points. The attractiveness of each POI is measured by an enhanced two-step floating catchment area (ES2FCA) method (Shi, Alford-Teeater, Ongena, & Wang, 2012; Zhao et al., 2017). In the first step, for each pick-up or drop-off point (Lk), each POI (P_i) is given a weighted activity-to-POI ratio (R_i,k) according to the distance between the given POI and the pick-up or drop-off point. In the second step, the attractiveness of a POI (A_i) is calculated by summing all R_i,k referred to all the Lk. The second factor is measured by considering the attractiveness of a POI and the distance decay effect, which is expressed as

\[ \text{Pr}(x,y|P_i) \propto A_i \cdot e^{-\beta d(x,y)} \]  

where \( A_i \) is the attractiveness of POI \( P_i \), \( d(x,y) \) is the distance between the given location and \( P_i \), \( \beta \) is the distance decay coefficient. Here, we set \( \beta = 1.5 \) (Zhao et al., 2017).

The temporal attractiveness of activities at both origin and destination of each trip are represented by the visitation probability of activities, which are calculated based on the MOBIS survey data. The end time of activities in the MOBIS data can be regarded as the start time of micro-mobility trips, which are used to calculate origin activities’ temporal attractiveness. Similarly, the destination activities’ temporal attractiveness are calculated by using the start time of these activities in the MOBIS data.

where \( A_i \) is the attractiveness of POI \( P_i \), \( d(x,y) \) is the distance between the given location and \( P_i \), \( \beta \) is the distance decay coefficient. Here, we set \( \beta = 1.5 \) (Zhao et al., 2017).

**4.2.3. Calculating POI visit probability**

Bayesian rule is adopted to measure the visiting probability for each candidate POI. Specifically, given an origin or destination \( S = (x,y), t \) and a list of candidate POIs, the visit probability of candidate POI \( P_i \) is defined as follows:

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Fig. 4. Percentage of trips with at least one candidate POI for micro-mobility in different walking distance threshold.

Fig. 5. Visitation probability for each type of activity during different hours.
8

\[
\Pr(P_i|(x, y), t) = \frac{\Pr((x, y)|P_i, t)\Pr(P_i|t)\Pr(t)}{\Pr((x, y), t)} \tag{2}
\]

Generally, the location and the time can be considered independently given \( P_i \), namely \( \Pr((x, y)|P_i, t) = \Pr((x, y)|P_i) \), denoted as spatial attractiveness. \( \Pr(P_i|t) \) represents an activity time attractiveness. For origin, it is the probability that an activity finished at the origin time. With regards to the destination, it is the probability an activity happens at the end of the trip. Both \( \Pr(t) \) and \( \Pr((x, y), t) \) are constant values for a given point. Thus, the visit probability can be reformulated as

\[
\Pr(P_i|(x, y), t) \propto \Pr((x, y)|P_i)\Pr(P_i|t) \tag{3}
\]

### 4.2.4. Determining the activity type of origin and destination

For an origin or destination, the visit probability of all the candidate POIs can be calculated following Section 4.2.3. The visit probability for each activity is denoted as

\[
\Pr_{\text{Act}} = \frac{\sum_{P_i \in \text{Act}} \Pr(P_i|(x, y), t)}{\sum_{P_i \in \text{Act}} \sum_{P_i \in \text{Act}} \Pr(P_i|(x, y), t)} \tag{4}
\]

It should be noted that, instead of selecting a particular activity, the probabilities of all activities are utilized to represent the activity type of the given origin or destination.

Fig. 6. The spatial distribution on micro-mobility daily trip volume for different types of micro-mobility services. The blue bar and beryl green bar are the daily trip numbers in Normal period (\(N_{NP} \)) and Lockdown period (\(N_{LD} \)), respectively. The background color of each PLZ represents the ratio of the daily trip number in Lockdown and Normal period (\(N_{LD}/N_{NP} \)) for the given PLZ. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(a) Docked bike

(b) Docked e-bike

(c) Dockless e-bike
5. Results

5.1. Spatial and temporal analysis

5.1.1. Spatial changes on micro-mobility

In this section, we explore how micro-mobility patterns change over space for the three types of services during the Normal and Lockdown period. The 31 postcode areas (PLZ) in the study area are adopted as the primary spatial units, representing an administrative division of the study area, and reflect the underlying contextual information of each sub-region, such as population and land use type. Therefore, the spatial analysis focuses on examining how the trip volume varies across the postcode areas during the two periods. To cope with this problem, we assign the daily trip volume to the corresponding PLZ for the three types of micro-mobility services respectively. Fig. 6 shows the average daily volume of trips by PLZ for the three types of services, which are aggregated according to the drop-off points of trips. The blue and beryllium green bars indicate the daily trip volume in the Normal and Lockdown periods, which are denoted as $N_{NP}$ and $N_{LD}$ respectively. The background color represents the ratio of the daily trip volume in the Lockdown to the daily trip volume in the Normal period for the three types of services, which is expressed as $\frac{N_{LD}}{N_{NP}}$.

As shown in Fig. 6, the three types of micro-mobility services present some similar patterns between Normal and Lockdown periods. First, compared with the Normal period, the daily trip volume declines to varying degrees for most of the PLZs for the three types of services during the Lockdown period. Especially, the significant decreases are mainly concentrated in the central regions, such as PLZ 8001, 8002, 8003, and 8004, and 8005, which has more Shopping, Leisure, Transport, and Work POIs compared with other PLZs. In the Normal period, these POIs attract more passengers for various activities than other PLZs. However, during the Lockdown, most people started working from home and reduced the travel to avoid coronavirus exposure. Thus, an obvious change of the daily trip volume for the three types of services can be observed in central regions. Second, the trip volume in some PLZs displays a slight decrease or even increase during Lockdown period, such as PLZ 8046, 8051, and 8152. One possible explanation is that most POIs in these PLZs are residence and the proportion of Home related activities increased during the Lockdown period, as they are not influenced too much by the lockdown. Third, no trips are detected within the several peripheral PLZs of the study area for the three types of services, namely morning peak (7:00–8:00 AM) and evening peak (4:00–5:00 PM) on workday, which match well with the commuting patterns. It denotes that the trips for commuting could account for a high proportion of all the biking trips. Second, there is only one peak (1:00–3:00 PM) for the three types of services on weekends, which is lower than the two peaks during workdays. During the Lockdown period, it can be observed that: (1) There are still one morning peak and evening peak on weekend, while the two peaks are not so conspicuous as on Normal weekdays, especially the morning peak. It suggests that the decline of trip volume can be attributed to the lockdown regulation and most people working from home. For those who need to go to workplaces, the working hours have become flexible. (2) There is still one weekend peak, which has no significant change. However, compared with remarkable reduction of average trip volume between Normal and Lockdown workday, the average trip volume on weekend has no obvious change. Especially the volume of docked bike, the curve of NP workday almost coincide with the curve of LD workday. Overall, we can conclude that the striking difference between the Normal and Lockdown period is the travel declines in the peak hours of workdays for the three types of micro-mobility services.

We also analyze the trip duration distribution during the four periods. For each type of service, the OD data are divided into four groups based on the sub-periods. In each group, the distribution of trip duration is plotted by the violinplot function of the seaborn library, which is a combination of boxplot and kernel density estimate. Furthermore, to assess the variation in the Normal period and Lockdown period statistically, we employ a t-test to examine the difference between periods for each type of service, as displayed in Table 4.

As illustrated in Fig. 8, the solid white lines represent the medians and the dashed white lines are the quartiles. First, it can be observed that the statistics of trip duration distributions on Normal workday are lower than those on Lockdown workday correspondingly for the three types of services. Likewise, the similar conclusion can be reached on Normal weekend and Lockdown weekend for the three types of services. It is demonstrated that the trip duration in Lockdown period is on average higher than Normal period on both workday and weekend for the three bike (e-bike) services. In addition, the kernel density curve on Normal workday or weekend is shown to be taller and thinner than that on corresponding Lockdown workday and weekend for the three types of services. It also indicates that the proportion of trips with long duration increased during Lockdown period for the micro-mobility services. We conclude that people tend to ride bike (or e-bike) longer during the Lockdown period. Also, although the trip duration distributions for the micro-mobility services have changed from the Normal to the Lockdown period, these changes are mainly for the trips over 20 min. We further apply a t-test to examine the difference between the means of trip duration on Normal workday (or weekend) and Lockdown workday (weekend) for each type of service. As displayed in Table 4, all the

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2 https://seaborn.pydata.org/index.html.
The changes in Fig. 8 are significant at the 0.01 significance level. We further explore the trip distance distribution during the four specific periods, which reflects how far users travel using micro-mobility services. In a similar manner, Fig. 9 displays the trip distance distribution during the four sub-periods for the three types of micro-mobility services. First, it is reported that the docked bikes mainly serve the trips less than 2 km compared with docked and dockless e-bikes. This is because people can ride docked and dockless e-bikes for longer trips due to electric power. Second, as can be seen from Fig. 9, the statistics of trip distance distribution on Normal workday (or weekend) are also lower than those on Lockdown workday and weekend for each type of service. The trip distance in Lockdown period is on average longer than Normal period on both workday and weekend for the three types of services, which is in accordance with the conclusion drawn from Fig. 8. Third, the kernel density estimation results also illustrate that the proportions of the trips more than 2 km increased during Lockdown period for all the three micro-mobility services.

### Table 4

| Period 1 | Period 2 | Docked bike | Docked e-bike | Dockless e-bike |
|----------|----------|-------------|---------------|----------------|
| NP       | LD       | <0.01***    | <0.01***      | <0.01***      |
| NP workday | LD workday | <0.01***    | <0.01***      | <0.01***      |
| NP weekend | LD weekend | <0.01***    | <0.01***      | <0.01***      |

*, ** represent the significance at the 0.1, 0.05 level, respectively. *** represents the significance at the 0.01 level.

5.2. Network construction and spatial network characteristics

As described in Section 4.1 on spatially embedded network construction and spatial network analysis, spatial interaction network can be constructed based on origin-destination movement flow matrix calculated from the micro-mobility data. Fig. 10 displays the spatial interaction networks before and during the lockdown period for the three types of micro-mobility services. The size of red point represents the strength of each node, and the width of green line denotes the number of trips occurring between the two corresponding nodes. For each type of micro-mobility service, the node and link share the same legend scale in the two periods. First, it can be observed that most links of the network become thinner during the Lockdown period for the identical type of micro-mobility service. It could be attributed to the reduction of non-essential travels due to the implementation of the lockdown policy in Switzerland. Second, it is also found that several nodes become smaller during the Lockdown period for each type of service, which implies that the numbers of connections between those PLZs and other PLZs decreased compared with the Normal period. These nodes are mainly distributed in the city center, such as PLZ 8001, 8002, 8003, 8004, and 8005, which contain a large amount of shopping and entertainment facilities and the Zurich Main Station. Influenced by the pandemic, the number of trips to city center decreased significantly due to the reduction of unnecessary activities (e.g., entertainment and leisure). It should be noted that although the nodes with higher degrees and the links with higher weights of the three networks during the Normal period become smaller and thinner in the corresponding networks during the Lockdown period, the number of nodes and links do not change between the two periods. We can speculate that the micro-mobility services still play a significant role in...
Fig. 8. The distribution of trip duration in each period. The curve of each patch represents kernel density estimation of trip duration. The solid white lines are medians of the trip duration. The dashed white lines from bottom to top are the first and third quartile of the trip duration.

(a) Docked bike
(b) Docked e-bike
(c) Dockless e-bike

Fig. 9. The distribution of trip length in each period. The curve of each patch represents kernel density estimates of the trip length. The solid white lines are median of the trip duration. The dashed white lines from bottom to top are the first and third quartile of the trip duration.

(a) Docked bike
(b) Docked e-bike
(c) Dockless e-bike
human travel during the Lockdown period even if the number of trips decreased compared with the Normal period.

Note that for ease of interpretation and understanding, the difference of networks between Normal and Lockdown periods for each type of micro-mobility service is plotted, as shown in the Appendix (Fig. 11). The red color symbolizes the decrease of the number of interactions while the green color represents an increase. The figures further illustrate the substantial decrease of the number of interactions during the Lockdown period for the three types of services.

Moreover, we quantify the changes in micro-mobility patterns by calculating the network properties, as shown in Table 6. From the table, some changes between the Normal and Lockdown period can be recognized: (1) the number of nodes that represents the number of PLZs served by bikes and e-bikes are identical during the periods for each type of micro-mobility service, which implies that the service areas of micro-mobility modes have not been influenced by the pandemic. (2) the numbers of edges increased for the docked bike and e-bike services, while decreasing for the dockless e-bike service. The PLZs within the study area became more connected through intra-urban micro-mobility during the Lockdown period. The causes of the increases for docked bike and e-bike services are probably that some people selected the two types of micro-mobility services for their travels as the substitute for public transportation. Compared with the fixed stations of docked bike and e-bike within central areas, dockless e-bikes can be parked almost anywhere. Considering the reduction of human travel during the Lockdown period and the small number of dockless e-bikes within the study area, we speculate that the decrease for dockless e-bike service could be interpreted as its low circulation during the Lockdown period. For example, the e-bikes that were parked at the less populated areas may be lost to the users for a long period. (3) Similarly, the increased average degrees of the docked bike and e-bike networks during the Lockdown period also show the higher connectivity. For example, Fig. 10a-d show that the number of links to PLZ 8052 increases from the Normal period to the Lockdown period. (4) The decreased average strength for the three networks during the Lockdown period further quantitatively depicts the reduction of human travels by micro-mobility services. (5) Given that the number of nodes is unchanged for each type of micro-service network, the change of graph density is consistent with that of node edges.

Overall, these results suggest that the docked bike and e-bike mobility networks became denser during the Lockdown period, while the dockless e-bike mobility network became slightly sparser even if the numbers of trips decreased significantly for the three types of micro-mobility services.

### 5.3. Semantic analysis for different types of trips

Table 5

| Period 1 | Period 2 | Docked bike | Docked e-bike | Dockless e-bike |
|----------|----------|-------------|---------------|-----------------|
| NP       | LD       | <0.01***    | <0.01***      | <0.01***        |
| NP workday | LD workday | <0.01***    | <0.01***      | <0.01***        |
| NP weekend | LD weekend | <0.01***    | <0.01***      | 0.05*           |

*a*, ** represent the significance at the 0.1, 0.05 level. *** represents the significance at the 0.01 level.

In this section, we further explore the micro-mobility changes from the perspective of semantics by analyzing trip purpose (or activity type). After recognizing the activity types of origin and destination for each trip, we calculate the shares of human activities in each period for the three types of micro-mobility services, as displayed in Table 7. Specifically, both the Origin and Destination activities are investigated respectively for all the trips. In each block, the NP and LD columns represent the share of an activity in Normal and Lockdown periods for the origin or destination, denoted as $S_{NP}$ and $S_{LD}$ respectively. The Ratio columns further quantify how the share of each activity changes between the Normal and Lockdown periods, which can be calculated by $(S_{LD} - S_{NP})/S_{NP}$. Note that the table is ranked by the share of activities for docked bike service in the Normal period.

As shown in Table 7, the activity types of most origins and destinations are concentrated in Home, Work, Transport and Leisure for the three types of micro-mobility services, which account for approximately 80% of all the trips in both periods. However, the rankings of these activities are not stable according to the shares. For docked bike service, it can be observed that Leisure (20.5%) occupies first place in Origin activities during the Normal period, then Work (19.9%), Transport (19.5%), and Home (17.7%) follow successively. In the Lockdown period, the proportions of Home (19.8%) increase while those of Leisure (17.8%) and Work (16.7%) decrease in Origin activities. It can be interpreted as that the time people staying at home becomes longer during the Lockdown period, thus more origins are home-related. For the Destination activities of docked bike service, Home achieves the highest share in both Normal and Lockdown period, namely 23.7% and 21.8%. The next ranks are Transport, Leisure, and Work for the two periods. It should be noted that the proportions of Leisure decreased for both Origin and Destination activities during Lockdown period, which demonstrates that people exactly reduced their Leisure activities to keep social distancing during the lockdown. Also note that Leisure and Park are the activities for entertainment, and the main difference between them is Leisure here is for indoor activities while Park is mainly for outdoor activities. Another interesting point is that the proportions of Grocery and Park increased for both Origin and Destination activities during the Lockdown period, which can be explained from two aspects. On the one hand, people spend more time staying at home during Lockdown period (e.g., working from home), and then consume more daily necessities correspondingly, which implies that more Grocery activities are required for the people during this period. On the other hand, considering the long time staying at home, parks are better choices for relaxation and exercises during the Lockdown period compared with the indoor places (e.g., bars, gymnasiums). These conclusions also conform with the COVID-19 Community Mobility Report regarding Zurich from Google.

Meanwhile, although docked e-bike service shares the same docking stations with docked bike service, Transport and Home occupy the first and second place, respectively, when they are as Origin and Destination activities during the two periods. Regarding Leisure, Grocery and Park activities, we can observe the similar changes and reach the same conclusions as docked bike service. With regard to dockless e-bike service, Home as both Origin activity and Destination activity plays a dominant role in both periods, which can occupy at least 35% of all the trips. Work is the following Origin activity in both periods, which reveals that most dockless e-bike trips are from these two types of activities. However, Transport is in the second place for the Destination activities during the two periods. Compared with the two types of docked services, Home activities show higher proportions and Transport activities display lower proportions during the two periods. One possible explanation is that people may select dockless e-bike as the transport mode for first or last mile travel. Considering that many docking stations are located around the tram and bus stations in Zurich, people can only pick-up and drop-off the bike (or e-bike) in those fixed docking stations, and then complete the next activities using docked services.

With regards to the Ratio columns in Table 7, the positive represents that the activity share increases, while the negative represents that the share decreases during the Lockdown period. First, it can be seen that the shares of Home increase for the three types of micro-mobility services except the share of Destination activity for docked bike. It further demonstrates that people started reducing the number of trips related to other activities, and stayed at home longer in Lockdown period. This is why the share of Home occupies a higher share in all the activities. We also note that the share of Home decreases as Destination activity for docked bike service. One possible explanation is that the docked bike and e-bikes share the
Fig. 10. Network construction for the three types of micro-mobility services during the two periods. The size of red dot represents the degree of the node. The width of green line represents the weight of the link. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
are not easy to get around the universities compared with docked services. It may be because dockless e-bikes are mainly located on the campuses of the universities in Zurich. It is convenient for students to travel to different leisure-related facilities that are enforced to be closed, such as bars, coffee rooms, gyms, and parks. The number of leisure activities decreases dramatically to keep social distancing. Similarly, the shares of shopping also display the decreasing tendency. Last, the proportions of grocery and park increase remarkably for the three types of service.

6. Discussion

Our findings have several important implications with respect to urban planning and policy recommendations. First, the results of spatial analysis and network analysis indicate that the overall demand of micro-mobility services is reduced during the Lockdown period, while a small amount of trip demand is still required between the PLZs. The bike sharing operators could consider reducing the supply of bikes and e-bikes in the market to save the idle resources during the Lockdown period, and the re-balancing of bikes and e-bikes is required to satisfy the necessary travels between the PLZs. In addition, for those regions with undulating terrains, the operators may consider placing more e-bikes rather than bikes. Second, the results of trip purpose analysis suggest that the proportions of grocery and park activities increase obviously during the Lockdown period. It would be meaningful for the policymakers to establish several outdoor sites near the residences to provide daily necessities (e.g., food, vegetables), which are beneficial for the citizens to further reducing the times of going out and lowering the potential risks of getting infected.

The space-time-semantic analysis in this study can facilitate understanding how micro-mobility services change in response to the COVID-19 pandemic. There are several limitations future research directions that we want to point out. First, we only consider the Normal period and Lockdown period. After the dataset over a longer period is obtained, more systematic and comprehensive micro-mobility changes will be investigated to discover more meaningful patterns and knowledge. Second, the same business hours are assigned to each type of POI based on their typical business hours in the study area, as displayed in Table 2. The obtained business hours of POIs are still coarse, which might influence the accuracy of trip purpose imputation. Third, the study period...
rages from February to April in 2020. The time period contained various weather conditions, such as rainy days and sunny days, which could influence the number of trips. The Spring was coming and the temperature was also getting higher, both increasing the willingness of people to ride a bicycle. Forth, the micro-mobility changes in response to the COVID-19 pandemic are also associated with other factors, such as population, economy, policy, and culture. The empirical results from this study may only reflect the reaction of Zurich or Swiss cities. If possible, more case studies will be analyzed in different cities with various situations, which could provide additional insights into understanding micro-mobility changes and providing suggestions if another pandemic may occur in the future.

7. Conclusion

In this study, we investigate the changes of micro-mobility patterns before and during lockdown period by analyzing the trip data of three types of micro-mobility services (i.e. docked bike, docked e-bike and dockless e-bike) in Zurich, Switzerland. Specifically, we characterize the changes of micro-mobility from the perspective of space, time and semantics. The major conclusions of this study are summarized as follows.

First, spatial and temporal analysis are conducted to explore how the number of trips changes for each type of micro-mobility service over space and time. The spatial analysis results suggest that the three types of services display some similarities and differences in terms of the micro-mobility changes between the Normal and Lockdown period (See Fig. 6). On the one hand, the daily trip volume decreases with varying degrees for most of the PLZs for the three types of services during the Lockdown period. This is because that most people started working from home and reduced the unnecessary travels to avoid getting infected during the Lockdown period. On the other hand, docked and dockless e-bikes draw more attention than docked bikes in some PLZs with undulating terrains. The temporal analysis results reveal that the trip volumes show remarkable decrease on workdays, especially the peak hours, during the Lockdown period, while only slight changes are observed on weekends compared with the Normal period (See Fig. 7). It is indicated that working from home is the most important driving factor for the temporal changes of micro-mobility services. Therefore, these findings can be helpful for operators to regulate and rebalance the bikes and e-bikes in a city, especially in the circumstance of COVID-19 pandemic.

Second, the trip duration distribution and trip distance distribution are examined based on statistical analysis for the three types of services on weekdays and weekends during the Normal and Lockdown period. From the trip duration distribution result (See Fig. 8), the statistics of trip duration on Normal weekday and weekend are lower than those on Lockdown weekday and weekend, which indicates that the trip duration in Lockdown period is higher than that of the Normal period on average for the three types of services. Especially, the proportion of long-duration travels by micro-mobility services increases during the Lockdown period. The trip distance distribution result (See Fig. 9) shows a similar pattern as trip duration distribution. The proportion of medium- and long-distance travels (more than 1500 m) by micro-mobility services increases during the Lockdown period.

Third, spatial network analysis is implemented to understand the micro-mobility changes from the perspective of origin-destination flows for each type of service during the two periods. By constructing the spatially embedded networks for each type of the service and compare them during the two periods, it is found that the numbers of links of the networks during the Lockdown period do not decrease compared with the networks during the Normal period, while the links become thinner for each type of service. It is indicated that the movements by micro-mobility services between the PLZs have not been interrupted completely due to COVID-19 pandemic, while the numbers of trips between the PLZs are definitely reduced. This is because people reduced their daily trips due to the pandemic and the Swiss Lockdown regulations. However, the Swiss government did not implement the Lockdown regulations to each PLZ and each city. Hence, there are still several trips that occur between the PLZs. The network indicators further quantify these micro-mobility changes for each type of service during the two periods.

Last, trip purpose analysis is used to examine the micro-mobility changes from the perspective of semantics. A trip purpose imputation framework is developed to recognize the activity type of origin or destination for the three types of micro-mobility services based on the existing trip purpose prediction methods. By comparing the changes of origin and destination types for each type of service, the results illustrate that Home, Work, Transport and Leisure activities occupy about 80% of all the trips during both Normal and Lockdown periods, while the rankings of these activities are not stable for each type of service. We further define a share of purpose based metric to quantify how the activity types of origin and destination change during the two periods for the three types of services. It is found that the shares of Home increase for the three types of services indicating the reduction of other types of activities, which is consistent with the existing findings of recent studies and reports. Another interesting finding is that the shares of Leisure decrease while the shares of Grocery and Park increase remarkably during the Lockdown period for the three types of services. The decreases of Leisure shares suggest that the number of leisure activities are reduced as almost all the leisure-related facilities are enforced to be closed during the Lockdown period. The increases of Grocery and Park shares indicate that people may go out more times for grocery shopping, select parks as the places for relaxation and exercises during the Lockdown period due to working from home.

In summary, by analyzing the rapidly evolving trip patterns of micro-mobility in response to COVID-19, this research can help planners and policymakers better make evidence-based policies regarding micro-mobility in the post-pandemic society. Moreover, exploiting high-resolution micro-mobility trip data and implementing the proposed spatial-temporal-semantic methodology, the city authorities and the service providers can continue to closely monitor micro-mobility for the effective deployment of the fleets in cities. This is particular relevant in the post-pandemic society as many cities worldwide are considering expanding the deployment of micro-mobility to support a ‘green’ restart of local travel and help mitigate reduced public transport capacity (GOV.UK, 2020).

Declaration of Competing Interest

The authors declare no conflict of interest.

Acknowledgements

This research has been supported by the QR Strategic Priorities Fund provided by Research England. The authors are thankful to Roll2Go AG for collecting the micro-mobility trip data used in this research as specified in Section 3.1.

Appendix A. Supplementary results
Fig. 11. The changes of spatial networks for the three types of micro-mobility services between Normal and Lockdown periods. A node $N_i$ denotes a sub-region, whose centroid coordinate ($x_i$, $y_i$) is regarded as the spatial location of the node. The edges represent the change of trips between the two nodes from the Normal period to the Lockdown period. The red link represents the number of trips between two nodes decreases while the green link represents the number of trips between two nodes increases.

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