Analysis of spatiotemporal mobility of shared-bike usage during COVID-19 pandemic in Beijing

Xinwei Chai¹,² | Xian Guo¹ | Jihua Xiao² | Jie Jiang¹

¹School of Geomatics and Urban Spatial Informatics, Beijing University of Civil Engineering and Architecture, Beijing, China
²BeiDou Navigation & LBS (Beijing) Co., Ltd, Beijing, China

Correspondence
Xian Guo, School of Geomatics and Urban Spatial Informatics, Beijing University of Civil Engineering and Architecture, no. 15 Yongyuan Road, Daxing District, Beijing 102616, China. Email: guoxian@bucea.edu.cn, guoxian@lreis.ac.cn

Funding information
National Key R&D Program of China, Grant/Award Number: 2018YFB2100701; Research Program of Beijing Advanced Innovation Center for Future Urban Design, Grant/Award Number: UDC2019031321; The Pyramid Talent Training Project of Beijing University of Civil Engineering and Architecture, Grant/Award Number: JDYC20200322; National Natural Science Foundation of China, Grant/Award Number: 41601389

Abstract
The entire world is experiencing a crisis in public health and the economy owing to the coronavirus disease 2019 (COVID-19) pandemic. Understanding human mobility during the pandemic helps to formulate interventional strategies and resilient measures. The widely used bike-sharing system (BSS) could illustrate the activities of urban dwellers over time and space in big cities; however, it is rarely reported in epidemiological research. In this article, we analyze the BSS data to examine the human mobility of shared-bike users, detecting the key time nodes of different pandemic stages and demonstrating the evolution of human mobility owing to the onset of the COVID-19 threat and administrative restrictions. We assessed the net impact of the pandemic using the results of co-location analysis between shared-bike usage and points of interest. Our results demonstrate that the pandemic has reduced overall bike usage by 64.8%; however, a subsequent average increase (15.9%) in shared-bike usage has been observed, suggesting partial recovery of productive and residential activities, although far from normal times. These findings could be a reference for epidemiological research, and thereby aid policymaking in the context of the current COVID-19 outbreak and other epidemic events at the city scale.

1 | INTRODUCTION

Coronavirus disease 2019 (COVID-19) is a rapidly spreading infectious disease caused by the novel coronavirus SARS-COV-2, which has now triggered a global pandemic (https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-cause
Based on a situation report by the WHO (https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200422-sitrep-93-covid-19.pdf), the worldwide total confirmed cases have reached 2,471,136, including 84,287 in China as of April 22, 2020. The COVID-19 pandemic made a huge impact on public health and most economic sectors, from the beginning of the Chinese New Year holiday until May 2020. Under the threat of the pandemic, the productive and social activities of residents were inevitably influenced (Akter & Wamba, 2019; Wang, Chen, Wang, & Baldick, 2016). Measuring the changes in human mobility dynamics is essential for transmission prediction, control measure design, and post-pandemic recovery.

Current COVID-19-related epidemiological studies mainly focus on transmission dynamics (Li et al., 2020; Pitzer et al., 2009) and preventive measures (Chinazzi et al., 2020; Hazel et al., 2006; Van Den Boulos & Geraghty, 2020) from a local or global perspective (Mollalo, Vahedi, & Rivera, 2020; Yang et al., 2020). Nevertheless, a few studies have investigated the spatiotemporal dynamics quantitatively during the pandemic. Ferguson et al. (2020) has studied two main strategies of non-pharmacological interventions in infectious disease prevention: (1) suppression, corresponding to the case of China and South Korea, with enormous social and economic costs, which may cause secondary adverse impacts on health and well-being in the short and long term; (2) mitigation, corresponding to the case of the United Kingdom and the United States, which may not be able to protect residents at risk from severe disease, resulting in high mortality. Fang et al. (2020) provided a causal interpretation of the impact of the city lockdown on human mobility and the spread of COVID-19 in China. Mollalo et al. (2020) developed nationwide geographic modeling of COVID-19 and investigated the county-level variations of COVID-19 incidence across the United States. With the help of the mobile internet user data from the Baidu Mobility platform, Mu et al. (2020) examined the relationship between COVID-19 disease spread and inter- and intra-city mobility in 319 Chinese cities. However, few studies have focused on the dynamics of human mobility at local scales during a long-term pandemic.

Geospatial big data have great potential in the improvement of disease surveillance and disaster response (Goodchild & Glennon, 2010; Horanont, Witayangkurn, Sekimoto, & Shibasaki, 2013; Huang, Li, Liu, & Ban, 2015; Yu, Yang, & Li, 2018). To explore the effect of the COVID-19 pandemic on the spatiotemporal changes in human mobility, state-of-the-art approaches use VGI (volunteered geographical information) as an important data source.

- Social media: research on Weibo (mainstream microblog social media in China) (Yin, Lv, Zhang, Xia, & Wu, 2020; Zhao, Cheng, Yu, & Xu, 2020) explores public attention and information propagation on social networks; Facebook “Data for Good” is proved to carry additional location information which is helpful to evaluate the risk of future COVID-19 outbreaks (Chang et al., 2021). However, geo-tagged posts comprise a small part of the whole data, and do not reflect people’s routines.
- Mobile phone data-related studies in Shenzhen, China (Zhou et al., 2020), Tokyo, Japan (Yabe et al., 2020), and the whole of the United States (Xiong, Hu, Yang, Luo, & Zhang, 2020) confirm the positive relationship between human mobility and COVID-19 infections, but one can scarcely distinguish purposeful movements from random wandering/indoor movements in these data.
- Navigation data from mapping platforms: studies based on Google Maps (Li et al., 2021) and Baidu Maps (Huang et al., 2020) reveal transportation-related behaviors with navigation data. For the same reason as in social media, navigation data cannot cover regular short movements.

Owing to the aforementioned reasons, the widespread bike-sharing system (BSS) in China becomes an alternative for fulfilling people’s need for regular short-distance transportation, and it became a data source for analyzing human mobility at city scale during the pandemic period. Following the COVID-19 outbreak, social distancing and home quarantine were imposed for the prevention of the pandemic. Additionally, there was a suspension of buses and taxis for a short period following the outbreak, since vehicles comprised a public enclosed space. These strict control measures inevitably narrowed the options for public transit.

Thanks to the rapid development of GIS and Internet of Things (IoT)-based systems, the third-generation BSS (free-floating/dockless BSS) emerged in China in 2015. Compared to its predecessors, the third-generation BSS...
(from now on referred to simply as BSS) is no longer limited by docking stations. It is often spread along roads and covers most urban dwellings. In the city of Beijing, for example, the number of shared bikes reached a peak in 2017 and the municipal government subsequently began to eliminate excess bike supply (http://ebma-brussels.eu/bike-sharing-in-china/). Following 2 years of rapid development and regulation, BSS demand/supply reached a balance in 2019, which made it a stable data source.

BSS records contain origin–destination (OD) information and timestamps from anonymous users offering a promising alternative data source, revealing spatial and temporal information on the outdoor activities of residents. According to Daxue Consulting (https://daxueconsulting.com/mobike-and-ofo-bike-sharing/) in Beijing, 93% of trips less than 5 km are quicker by bike or public transport than by car. Chen, van Lierop, and Ettema (2020) stated that approximately half of the population in Beijing were registered as dockless shared-bike members in 2017, suggesting that this large user base and the easy access to shared bikes have made BSS data suitable for characterization of human mobility. Du and Cheng (2018) studied BSS travel patterns in Nanjing via limited questionnaires. Xu et al. (2019) characterized the temporal flow and spatial distribution of shared bikes in Singapore. Kaggle organized a competition for predicting shared-bike demand (https://www.kaggle.com/c/bike-sharing-demand) based on limited entries. Studies focusing on BSS rebalancing strategies also exist (Ai et al., 2019; Chen et al., 2016; Pal & Zhang, 2017). However, the use of BSS data in the studies of pandemic response is still in its early stages.

To address the lack of understanding of the spatiotemporal dynamics of city-scale human mobility influenced by the COVID-19 pandemic, we have formulated the following objectives:

1. Determining the pandemic period and measuring period-wise changes in human mobility.
2. Assessing the net pandemic impact and rehabilitation progress.

We managed to demonstrate spatiotemporal patterns intuitively and computationally.

- The intuitional part helps one to understand quickly the situation by showing a timeline, different phases of the entire pandemic, and basic statistics of the Point Of Interest (POI) categories, approximately revealing the severity of the pandemic.
- The computational part gives a more quantitative vision. We first divided the study period (January–March 2020) into several pandemic periods via a k-segmentation approach, which deduced the epidemic stages based on the temporal characteristics of human mobility from the BSS dataset. We subsequently assessed the net impact of the COVID-19 pandemic via a DID (difference-in-differences) model with the long-time-sequenced BSS data dating from 2019. Among numerous candidate explanatory variables, we eliminated the effect of Chinese New Year and the weather factor and quantified the impact of the epidemic on human mobility. Finally, during the different pandemic periods, we implemented a co-location analysis between shared-bike usage and the different types of POI, which demonstrated the evolution of mobility due to the onset of the COVID-19 threat and assessed rehabilitation progress related to different urban functions.

The main novelty of our work is the quantification and assessment of the net impact of the COVID-19 pandemic on overall cities (outside the outbreak zone) from a spatiotemporal perspective via the human mobility extracted from long-time-sequenced shared-bike records. To our knowledge, no previous study has investigated the impact of epidemics based on BSS data. The results are at city level, which could provide fine-scaled references for policymaking and epidemiological research.

The remainder of the article is organized as follows. Sections 2 and 3 describe the study area and research methods. Section 4 reports the spatiotemporal characteristics of shared-bike usage and reveals the DID results. Section 5 presents a co-location analysis with POIs, which quantifies the pandemic influence and the degree of rehabilitation toward different urban functions. Section 6 concludes with pertinent remarks and Section 7 states the outline of our future research.
2 | STUDY AREA AND DATA

2.1 | Study area

This study was conducted in the city of Beijing, the capital of China. As shown in Figure 1, Beijing is located on the North China Plain, occupying an area of 16,411 km² (39.4–41.6°N, 115.7–117.4°E). By 2019, the urban population of Beijing had reached 21.53 million. The cumulative total COVID-19 confirmed cases in Beijing had reached 418 by March 5, 2020 (http://wb.beijing.gov.cn/home/ztzl/kjyq/fk_yqtb/202003/t20200305_1681121.html). As a metropolis with a huge population of immigrants, Beijing had taken measures in response to the outbreak, such as a holiday extension and executive orders like "stay at home" and "working from home". Under these circumstances, human mobility was influenced, showing spatiotemporal patterns different from normal times.

2.2 | Datasets

Four datasets were used in our study: BSS records, POIs, confirmed COVID-19 cases, and weather records.

2.2.1 | BSS records

This OD dataset came from 1.02 million shared bikes belonging to four main BSS operators (Mobike, DiDi Bike, Hellobike, and Ofo) in Beijing. The records date from March 2019 to March 2020 (66.8 GB) and cover 1.5 million uses per day contributed by 11 million users, accounting for half of the total population of Beijing. They were created when users locked/unlocked their shared bikes, excluding rebalancing operations. This exclusion guarantees that records were collected purely from users. Moreover, the BSS data are anonymous, so there are no privacy concerns. It should be noted that the BSS records in certain districts (Chaoyang, Fengtai, and Shijingshan) are not available due to the different policies of local governments.

FIGURE 1 Study area (left) and 87 confirmed infected cases in Beijing by March 5, 2020 (right)
2.2.2 Points of interest

Beijing POIs were collected from the AutoNavi API provided by Gaode Maps (https://opendata.pku.edu.cn/datasset.xhtml?persistentId=doi:10.18170/DVN/WSXCNM), one of the most popular web-mapping platforms in China. Each entry has a unique POI ID, object_id, an address including longitude/latitude information, and a three-level category: large_category, mid_category, and sub_category. Among the hundreds of categories, we chose seven mid ones: residential area (RA), high-tech company (HC), other company (OC), subway station (SS), shopping plaza (SP), supermarket (SM), and tertiary hospitals (TH). HC and OC reflect productive activities; SP, SM, and TH reflect social activities; and RA and SS reflect both types of activities.

2.2.3 Confirmed COVID-19 cases

The cumulative daily counts of clinically diagnosed cases in each district from January 20 to March 5, 2020 were collected from the daily update on the COVID-19 outbreak dashboard provided by the Foreign Affairs Office of the People’s Government of Beijing Municipality (http://wb.beijing.gov.cn/home/ztzlkjyq/). We selected a total of 87 infected residential areas (see Figure 1). According to the timeline (Li et al., 2020) of the outbreak, we visualized the evolution of the overall pandemic situation of Beijing in Figure 2.

2.2.4 Weather data

Weather data were obtained from the China Meteorological Data Service Center (http://data.cma.cn/en), containing daily weather information such as temperature, wind speed, and precipitation, dating from January 1 to March 5, 2019 and 2020.

3 TOOLS AND METHODOLOGY

3.1 Tools

In order to deal with large-scale spatial queries on the huge BSS dataset (66.8 GB), we had to apply parallel computing throughout this study:

1. HDFS (Hadoop Distributed File System, https://hadoop.apache.org/docs/r1.2.1/hdfs_design.html): a distributed file system which is suitable for parallel computing.

![Figure 2: Snapshots of accumulated confirmed cases in Beijing from January 25 to February 10, 2020](image-url)
2. Spark (https://spark.apache.org/): a parallel analytic engine for big data, which can invoke structured query language (SQL) to process temporal queries in the BSS data, performing denoising and statistical analysis.

3. GeoSpark (Huang, Chen, Wan, & Peng, 2017): a GIS-based engine based on Spark, capable of performing spatial analysis and visualization of geo-based data.

Python was our primary programming language, and cartographic visualizations were created using Esri’s ArcGIS 10.7 (https://www.esri.com/en-us/arcgis/about-arcgis/overview). All computations were run on a computer cluster consisting of seven machines with Intel® Xeon®, CPU E5-2640 v2 @ 2.00 GHz, 8 cores, 61.7 GB RAM, 20 MB cache.

3.2 Methodology

This study aimed to quantitatively analyze the impacts of COVID-19 on Beijing from a spatiotemporal perspective via the human mobility extracted from long-time-sequenced BSS data. Figure 3 shows the workflow of the present research. In the pre-processing block, the BSS data and other datasets were stored in a spatial database and denoised before use. Certain POI types were clustered using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm (Ester, Kriegel, Sander, & Xu, 1996), since they may be located close to each other causing duplicate patterns in further analysis. In the analysis block, there were mainly five tasks.

1. Statistical charts: a first-step visualization of the statistics of the shared-bike data.
2. Phase segmentation: using the k-segmentation approach to divide the entire study period into logical phases (i.e., pandemic phases).
3. Co-location analysis: measuring shared-bike usage near the different POIs in different phases.
4. Heatmap: visualization of the shared-bike data based on the aspect of space + time.
5. DID: quantitative analysis of the shared-bike data.

3.3 Data pre-processing

Our raw datasets require pre-processing for further analysis. We first removed the outliers (e.g., bikes “in the water,” temperature of 999°C, etc.). We also had to deal with duplicate positions. HC and OC are of high spatial density because multiple companies may co-locate in the same/adjacent office buildings. To avoid repeated counting of POI–bike co-located pairs, we used POI clusters for these three categories instead. We clustered nearby POIs using the DBSCAN algorithm, which has three advantages:

- specification of the number of clusters is not required;
- clusters of all forms and sizes are permitted; and
- noise and outliers are dealt with easily.

We configured the DBSCAN parameter as follows: \( \epsilon = 100 \) m, the maximum distance between two samples and \( \text{min} \_\text{samples} = 10 \), the number of samples in a neighborhood for a point to be considered as a core point of a cluster.

Among the seven chosen POI categories, RA is only the “area of interest” (not a “point of interest”). The RA records contain not only their geometric centers, but also their contours, which is a key factor for generating further results. To solve this problem and unify the input of the whole procedure, we used the buffer zones of the POIs to replace the original POIs in the co-location analysis.
3.4 | Co-location analysis

The co-location analysis depicts the co-location patterns of shared-bike usage with adjacent urban functions. We proceeded with the shared-bike data and the POIs with GeoSpark, which performs spatial queries via parallel computing on Spark. Among the numerous spatial queries, we utilized `spatial_join(geom1, geom2)`, which checks if the object `geom1` is inside `geom2` and `distance_join(geom1, geom2, dist)`, which checks if the distance of `geom1` and `geom2` is less than `dist`. Since these checks are partition-independent except for points near the borders of the partitions, the parallel portion is high if the data are well indexed.

3.5 | Phase classification

Generally, the evolution of an epidemic can be empirically divided into several stages according to the timeline of the outbreak. Apart from an empirical division, we segmented the study period (2 months) in a more logical way using a phase-classification strategy based on the temporal characteristics of human mobility from the BSS dataset. In machine learning tasks, one often aims to minimize the predefined loss function to formulate the best classification such that elements within the same cluster are similar and elements across clusters are different. Likewise, we tried to segment the study period into phases comprising the most similar patterns using $k$-segmentation.
Definition 1 (k-segmentation) Let \( X = \{x_1, x_2, \ldots, x_N\} \) be a time series of length \( N \). Given \( k \in \mathbb{N}, k < N \), and index set \( T = \{n_0, \ldots, n_k\} \) with \( n_0 = 0 \), \( n_k = N \), and \( \forall i, n_i < n_{i+1} \), a \( k \)-segmentation of \( X \) is the set of time series \( X_i = \{x_{n_i+1}, \ldots, x_{n_{i+1}}\} \) where \( 0 \leq i \leq k - 1 \).

To evaluate a \( k \)-segmentation, we use \( \sigma = \sum_{i=1}^{N} \sigma_i \) as the loss function, where \( \sigma_i \) is the standard deviation of division \( X_i \). The goal is to find the best \( T \) to minimize \( \sigma \) (i.e., \( \arg\min_T \sigma(T) \)). This problem can be solved at the complexity level of \( O(N^2k) \) (Terzi & Tsaparas, 2006). In case \( k \) and \( N \) are small, the optimum can be found via exhaustive search.

3.6 | Difference-in-differences

Normally, it is difficult to find and quantify all the factors of a certain event. DID is a technique which tries to mimic an experimental research design using observational study data by constructing a “treatment group” and a “control group,” under the assumption of a “common trend” (the two groups will follow the same trend if no treatment is done) (Card & Krueger, 1994). The treatment (effect) can be extracted since all the effects of common factors are included in the “common trend.” We applied DID to distinguish the impact of the epidemic effect from other effects (e.g., the effect of Chinese New Year). Table 1 shows the configuration of the DID analysis. Assuming we have a “virtual pandemic” just following the Chinese New Year of 2019, we set \( T \) and \( D \) as binary variables, with \( T \) indicating whether the year is 2020 and \( D \) indicating whether the study period is during the pandemic. The “real” pandemic is present only when \( T = 1 \) and \( D = 1 \).

By including the BSS dataset of 2019 as a control, the DID regression function is as follows:

\[
\log(U_t) = \alpha + \beta_1 \cdot \text{Before}_{2020,t} + \beta_2 \cdot \text{During}_{2020,t} + \theta_t + \epsilon_t
\]

where \( t \) is the date, \( U_t \) is the shared-bike usage on date \( t \). \( \text{Before}_{2020,t} \) and \( \text{During}_{2020,t} \) are dummy variables. \( \text{Before}_{2020,t} = 1 \) if \( t \) is 4 to 11 days before the outbreak of the pandemic. This term is set to verify the common trend assumption in DID analysis. \( \text{During}_{2020,t} = 1 \) when \( t \) is during the pandemic or in the mitigation period (corresponding to \( T \times D \) in Table 1). \( \alpha \) is a constant term, \( \beta_1 \) and \( \beta_2 \) are fitted coefficients, \( \theta_t \) is date fixed effects (weather, temperature, weekday/weekend, Chinese New Year, etc.), and \( \epsilon_t \) is the residual term. The effect of holiday and pandemic can be evaluated by \( \beta_1 \) and \( \beta_2 \).

4 | RESULTS

4.1 | Temporal characteristics of shared-bike usage

We chose several time points from the WHO statements (https://www.who.int/news-room/detail/27-04-2020-who-timeline---covid-19), as shown in Table 2. These important dates could track the virus transmission in Beijing.
Since the COVID-19 outbreak coincided with the Chinese New Year holiday in 2020, we used the Chinese New Year holiday of 2019 as a comparison to assess the influence of this period on shared-bike usage. It is worth mentioning that the Chinese New Year holidays of 2019 and 2020 were not of equal length, since that of 2020 was extended by executive orders. We compared the shared-bike usage during rush hours (8:00–09:00) over 64 days from January 1 to March 2, 2019 and January 1 to March 1, 2020, respectively (data of February 29 and March 1, 2020 were brought back by 1 day due to the leap year in 2020). We chose rush hours because these time intervals correspond to the highest shared-bike usage frequency of the day, and reflect productive activities. Figure 4 illustrates the temporal evolution of shared-bike usage during the selected periods of 2019 and 2020 (POI-wise graphs are given in Figure A1 of the Appendix).

As shown in Figure 4, shared-bike usage dropped sharply with the beginning of the Chinese New Year holiday. During these periods, schools and workplaces were closed. In 2020, the overall shutting of places was extended forcibly to mitigate the pandemic.

The shared-bike usage during rush hours exhibits a periodicity in productive activities: high on weekdays and low on weekends, which supports our general knowledge. However, this pattern did not match the week of February 10, 2020, when the government declared the partial restarting of certain productive and social activities. This anomaly suggests that the activities were not resumed until at least February 17, one week following the partial restart, corresponding to the fact that the impact of the pandemic lasted until the end of our study period.

Remark In this article, we assume that shared-bike usage follows a normal distribution, whose 95% confidence interval is \( \bar{x} - 2\sigma, \bar{x} + 2\sigma \), and data are presented in the form \( \bar{x} \pm 2\sigma \).

Table 3 presents a statistical view of aggregated bike usage during different time intervals. The upper part shows that during the rush hours of ordinary days, shared-bike usage in 2020 was of the same order of magnitude as that in 2019, suggesting that shared-bike demand follows common trends. However, the lower part depicts the case of the Chinese New Year holiday, where overall shared-bike usage dropped to less than 40% compared with the same period in 2019, suggesting that more companies stopped working due to the Chinese New Year holiday in 2020.

However, the dates in Table 2 may not be a proper segmentation, since there is no noticeable shared-bike usage change following February 10. We obtained a time series by computing the shared-bike usage within 100 m of each POI every day from January 2 to March 2, 2020. Then we segmented the time series into three phases in accordance with k-segmentation (see Definition 1). We found the best-classified phases at \((k, N) = (3, 62)\), with the minimum sum of standard deviation as metric via exhaustive search shown in Table 4. The COVID-19 transmission phases in Beijing can be identified as: before pandemic (phase a, before January 23), during pandemic (phase b, January 24–February 24), and pandemic mitigated (phase c, after February 25).
We also noticed a minor difference between the shared bikes around HC, OC, and others. This difference could be explained by the lag between the end of work and the start of vacation. Social and productive activities had not resumed until February 24, 2 weeks following the official declaration of the partial restart.

4.2 Spatiotemporal evolution of shared-bike usage

In this section, we first demonstrate the spatiotemporal change in shared-bike usage during the pandemic. Furthermore, a comparison of shared-bike usage between 2019 and 2020 was conducted to reveal approximately the influence of the pandemic in different phases. To evaluate its net impact, we applied the DID method to eliminate the influence of other factors (e.g., Chinese New Year, weather, and common trend of BSS data).

4.2.1 Evolution in 2020

Figure 5 shows the evolution of BSS activities during a 4-day interval from January 21 to March 2. The trend of human mobility is consistent with Figure 4.
Before January 21, 2020, shared-bike activities were spread throughout the city limits with a significant concentration in the downtown area (up to 500–1,000 records/hour). This pattern indicates the spatial distribution of human mobility before the COVID-19 outbreak.

After the outbreak, there was a dramatic drop in mobility following January 25, which was also the beginning of the Chinese New Year holiday. Figures 5b–e, ranging from January 25 to February 6, are dominated by low intensity, indicating that non-essential trips had dropped significantly due to the combined effects of holidays and the epidemic. This situation continued until February 9, when the spread of COVID-19 slowed and productive and social activities were allowed to restart partially.

**TABLE 4**

| Category | HC | OC | RA | SS | SP | SM | TH | Overall |
|----------|----|----|----|----|----|----|----|---------|
| Split point 1 | January 23 | January 23 | January 24 | January 24 | January 24 | January 24 | January 24 | January 23 |
| Split point 2 | February 24 | February 28 | February 24 | February 24 | February 24 | February 24 | February 24 | February 24 |

**FIGURE 5** Changes in distribution of shared-bike usage from January 21 to March 1, 2020. The daily shared-bike records were aggregated within 500-m grids and rendered with a color ramp from gray to green to red.
Figures 5f–k show a gradual increase in mobility from February 10 to March 1, 2020. However, human mobility was only restored to approximately 30% of the pre-pandemic level. It is worth noting that only slight differences could be observed between weekdays and weekends before February 17 and weekday–weekend oscillation reappeared after that date. There was higher demand for shared bikes on workdays in the downtown area than during the outbreak phase. However, this high demand was minimized on weekends, implying that residents were more inclined to reduce the risk of increased exposure by going outside under the threat of COVID-19.

4.2.2 Comparison between 2019 and 2020

Both the Chinese New Year holiday shutdown and the pandemic could have resulted in a mobility decrease. Hence, we compared shared-bike usage between 2020 and the same period of 2019. This procedure roughly eliminated the impact of the Chinese New Year holiday and reflected the influence of the pandemic in the whole study area.
Figure 6 delineates the sum of aggregated shared-bike usage in phases a, b, and c of 2020 (row 1), shared-bike usage in the corresponding period of 2019 (row 2), and the difference of the former two results (row 3). Figure 6d summarizes the average shared-bike usage intensity during the same time interval as phase a in 2019, showing similar spatial patterns as in 2020. Figure 6g shows the pre-pandemic difference of bike usage between 2019 and 2020, which is irrelevant to COVID-19. The increase and decrease in this subfigure is generally below 200 counts/hour, which could be due to inconsistencies and fluctuations of bike usage in different regions. We can conclude roughly that overall shared-bike usage remained in the same range during this phase over the past 2 years.

The significant discrepancies in shared-bike usage between 2019 and 2020 during phases b and c are considered a consequence of the COVID-19 pandemic. We traced the significant usage changes and showed, with fine-grained detail in Figure 7, that these areas were related to several well-accepted urban functional areas. According to Figure 6e, human mobility decreased due to the Chinese New Year in 2019, but a relatively high intensity remained in several well-accepted urban functional areas, such as Zhongguancun (Technology Park & Business zone), Shichahai (Tourism & Residential zone), Wangfujing (Tourism & Business zone), and Nancheng (Tourism & Residential zone). However, human mobility was in a state of complete suppression in 2020. The difference map in Figure 6h suggests that under the impact of COVID-19, trips were reduced for safety purposes.

Figure 6f indicates that mobility would instantly return to pre-festival levels or be more widespread, resulting from the influx of migrant employees following the holiday in 2019. According to Figure 6c, rehabilitation was in progress but much slower during the epidemic mitigation period. The remarkable difference inferred from Figure 6i verifies this sustained impact.

**FIGURE 7** Locations of significant usage changes recognized by annual shared-bike usage differences: (a) Xi’erqi (Technology Park); (b) Zhongguancun (Technology Park & Business); (c) Shichahai (Tourism & Residential); (d) Forbidden City & Wangfujing (Tourism & Business); and (e) Nancheng (Tourism & Residential)
4.3 | Estimation of pandemic impact via DID analysis

We applied the DID technique to quantify the impact of the pandemic by eliminating the influence of Chinese New Year, weather factors, and the common trend of shared-bike usage. We combined phases b and c in our DID model, since the pandemic lasted at least until the end of our study period.

Equation (1) was applied to measure shared-bike usage and weather data in the 62 days from January 1, 2019 and 2020, respectively. We used year 2020 as the treatment group and 2019 as the control group (no pandemic).

\[ \text{Before}_{2020} = 1 \text{ if } t \text{ is between January 1 and 10, 2020.} \]
\[ \text{During}_{2020} = 1 \text{ if } t \text{ is in phase b or c.} \]

The date range for \[ \text{Before}_{2020} \] is set to be unequal to \[ \text{phase a}, \] to avoid multi-collinearity problems. Otherwise, as the two variables cover all the study period, \[ \text{Before}_{2020} = 1 - \text{After}_{2020}, \] they are linearly dependent, which cripples the DID analysis.

Table 5 presents the regression results of Equation (1). We ignored the constant term \( a \) in the whole analysis, since we were more focused on the change in shared-bike usage, which reflects the human mobility of citizens. \( |\beta_1| \) is small enough, suggesting that the effects of Chinese New Year and the shared-bike usage trend are well absorbed by \( \theta \). \( \beta_2 \) is negative and statistically significant, suggesting that the pandemic reduced human mobility compared to 2019. We estimated the percentage of shared-bike usage decrease due to the net impact of the pandemic via \( 1 - \exp(\beta_2) \) (see Appendix). According to Table 5, the coefficient \( \beta_2 \) for all POI categories was \(-1.044\), which implies that the pandemic reduced overall bike usage by 64.8%. This percentage is slightly lower than the 69.49% estimated for Wuhan (the outbreak zone), as reported by Fang et al. (2020). Mu et al. (2020) estimated the intra-city mobility reduction in Beijing between 56.5% and 65.2%, which is consistent with our result (64.8%).

The same analysis was conducted in the seven POI categories. With all \( \beta_2 \) values at a 5% significance level, we considered that COVID-19 had a negative impact on mobility close/belonging to these types of urban functional areas. The main reason could be attributed to the quarantine restrictions. The estimated mobility reductions due to the pandemic of SS (77.91%), HC (74.21%), and SP (73.58%) were higher than those of other categories.

5 | CO-LOCATION ANALYSIS BETWEEN SHARED-BIKE USAGE AND POIs

To further explain the difference in the estimated mobility reduction of various aforementioned urban functions, we studied the relationships between the locations of different types of POIs and adjacent shared-bike usage with co-location analysis.

5.1 | Mapping POIs with shared bikes

Figures 8 and 9 take January 16, February 15, and March 2 as the profiles of phases a, b, and c, showing the position of our selected POI categories and the shared-bike usage in different pandemic phases. We selected SS and RA as typical POI categories for the following reasons:

- Shared bikes fulfill “first/last 1 km to/from subways” trips in normal times.
- However, during the pandemic, the flow of public transit was strictly limited and people were afraid of being infected, which may have caused a drastic decrease in subway usage.
- Moreover, to suppress disease transmission, intervention strategies—including work restrictions, home quarantine, and facility closure—were imposed, ensuring that people stayed at home, resulting in mobility being contained within residential areas.
|          | Overall | RA    | HC    | OC    | SS    | SP    | SM    | TH    | IRA   | SRA   |
|----------|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| $\beta_1$ | 0.033   | 0.011 | 0.051 | 0.023 | 0.027 | 0.005 | -0.01 | 0.017 | -0.066 | -0.074 |
|          | (0.066) | (0.069)| (0.114)| (0.100)| (0.084)| (0.166)| (0.083)| (0.067)| (0.076)| (0.067)|
| $\beta_2$ | -1.044  | -0.889| -1.355| -1.183| -1.51 | -1.331| -0.985| -0.886| -0.824 | -0.874 |
|          | (0.125) | (0.136)| (0.214)| (0.189)| (0.156)| (0.249)| (0.143)| (0.165)| (0.136)| (0.137)|
| $R^2$    | .921    | .906  | .894  | .892  | .911  | .687  | .824  | .916  | .884  | .902  |
| $1 - e^{\beta_2}$ | 64.80% | 58.89%| 74.21%| 69.36%| 77.91%| 73.58%| 62.66%| 58.77%| 56.13%| 58.27%|

Table 5: The net effects of COVID-19 on shared-bike usage obtained via DID, with values of During2020 ($\beta_2$) at 5% significance level, shown in the form $\bar{x} (\sigma)$. 

|          | Overall | RA    | HC    | OC    | SS    | SP    | SM    | TH    | IRA   | SRA   |
|----------|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| $\beta_1$ | 0.033   | 0.011 | 0.051 | 0.023 | 0.027 | 0.005 | -0.01 | 0.017 | -0.066 | -0.074 |
|          | (0.066) | (0.069)| (0.114)| (0.100)| (0.084)| (0.166)| (0.083)| (0.067)| (0.076)| (0.067)|
| $\beta_2$ | -1.044  | -0.889| -1.355| -1.183| -1.51 | -1.331| -0.985| -0.886| -0.824 | -0.874 |
|          | (0.125) | (0.136)| (0.214)| (0.189)| (0.156)| (0.249)| (0.143)| (0.165)| (0.136)| (0.137)|
| $R^2$    | .921    | .906  | .894  | .892  | .911  | .687  | .824  | .916  | .884  | .902  |
| $1 - e^{\beta_2}$ | 64.80% | 58.89%| 74.21%| 69.36%| 77.91%| 73.58%| 62.66%| 58.77%| 56.13%| 58.27%|
As shown in Figure 8, SS were always surrounded by large amounts of shared bikes. Although a drastic decrease in shared-bike usage could be observed during the quarantine period, some shared-bike usage remained around subway stations, which is consistent with Table 6. According to the figures corresponding to March 2, mobility started to recover following mitigation of the pandemic. As can be seen in Figure 9, infected RAs (IRAs) were mostly situated in the city center on January 16. On February 15, shared-bike usage around these IRAs was limited. On March 2, shared-bike usage had recovered nearly uniformly in the whole city, including IRAs and their surrounding areas.

To confirm the above observations, we performed a categorized co-location analysis with POIs as follows.

### 5.2 Estimating pandemic impact and rehabilitation progress using categorized co-location analysis

Different POI categories may co-locate with each other (e.g., RA and SM). To distinguish the type of shared-bike usage, we studied critical time slots (i.e., main shared-bike usage of each POI category). For instance, we selected 8:00–10:00 as the critical time slot for HC and OC.

Table 6 shows the shared-bike usage per day of approximately each POI category, with displacement of less than 100 m during the critical time slot, where the first three rows are cluster-based co-location, and the rest are point-based co-location. $U_p$, $U_o$, and $U_c$ denote shared-bike usage during phases a, b, and c. Two associated ratios measure the extent of the COVID-19 pandemic's effects: $U_p/U_o$ quantifies the decline in shared-bike usage during
Chinese New Year, which coincides with the quarantine period; $U_c/U_a$ reflects the progress of recovery (percentage of pre-pandemic shared-bike usage).

$U_b/U_a$ shows that the bike usage of all categories decreased to one-quarter that before the pandemic, and HC dropped the most in both values (from 4.06 to 0.42) and proportion (10.4%). One possible explanation is that the staff in HC comply most with the instruction to "work from home." During this period, intensive intra-city public traffic (e.g., buses) was restricted to avoid contact infection, and shared bikes were almost the only way to fulfill short-term travel demands in such a situation. $U_b/U_a$ of SM (25.2%), TH (24.7%), and RA (24.2%) are higher than those of other categories. One possible explanation is that for residents, the need for essential goods (e.g., food, medicine) could not be reduced, even though outdoor activities were voluntarily reduced during the quarantine.

$U_c/U_a$ shows that following the partial restarting of productive and social activities, bike usage in all categories recovered to some extent, but was far from the situation of normal times. The average increase in the seven chosen categories was 15.9% compared to phase b. Partial restart led to a slight increase in daily average shared-bike usage near HC and OC. $U_c/U_a$ of 28.6% for HC and 30.4% for OC suggests it was a long way from full recovery. During the mitigation period, SM had the highest recovery level, with $U_c/U_a$ up to 46.1%, because it served as the main subsistence suppliers.

In conclusion, HC and OC were greatly impacted from the beginning of the pandemic, coinciding with the Chinese New Year and people stopping work. SS was influenced to the same degree due to travel limitations and the threat of COVID-19.

Even if people had already stored sufficient supplies (usually, food storage was for 1 week or longer) to prepare for the Chinese New Year, they were running out of supplies and had to procure the necessities. Thus, RA and SM were less impacted following the 1 week of strict quarantine. SP was more influenced than RA and SM, because the goods provided by SP were mainly not necessities. TH had the smallest $U_c/U_a - U_b/U_a$ value among the POIs, suggesting that the THs were providing continuous services to the public during the pandemic.

In Figure 1, we noticed that being the center of Beijing, Dongcheng and Xicheng districts contained most of the IRAs, and the confirmed time lies between February 5 and 12. We carried out the same analysis on the

---

**TABLE 6** Bike usage in phases a, b, and c around the chosen POIs, shown in the form $\bar{x} \pm 2\sigma$

| POI category | Time slot | #POI (#cluster) | Bike usage per POI ($\times 10^3$) | Ratios $\bar{U}_a$ | $\bar{U}_b$ | $\bar{U}_c$ | $U_b/U_a$ (%) | $U_c/U_a$ (%) |
|--------------|-----------|-----------------|-----------------------------------|-------------------|------------|------------|----------------|----------------|
| RA           | All day   | 5,657 (1,204)   | 254.39 ± 133.76 61.65 ± 35.18 99.30 ± 5.59 | 24.20 | 39.00 |
| HC           | 8–10 hr   | 3,858 (81)      | 4.06 ± 3.52 0.42 ± 0.56 1.16 ± 0.15 | 10.40 | 28.60 |
| OC           | 8–10 hr   | 32,301 (577)    | 32.69 ± 26.68 4.19 ± 4.54 9.95 ± 1.11 | 12.80 | 30.40 |
| SS           | 8–22 hr   | 137             | 34.07 ± 21.57 4.25 ± 3.15 8.33 ± 0.61 | 12.50 | 24.50 |
| SP           | 18–20 hr  | 217             | 3.70 ± 2.01 0.79 ± 0.62 1.38 ± 0.15 | 21.30 | 37.20 |
| SM           | 18–20 hr  | 1,076           | 13.59 ± 7.63 3.43 ± 2.44 6.27 ± 0.58 | 25.20 | 46.10 |
| TH           | All day   | 86              | 13.69 ± 7.14 3.38 ± 1.79 5.00 ± 0.19 | 24.70 | 36.50 |
| Overall      | All day   | –               | 547.32 ± 301.74 124.02 ± 66.31 195.75 ± 10.43 | 22.70 | 35.80 |

**TABLE 7** Bike usage in phases a, b, and c around different RAs, shown in the form $\bar{x} \pm 2\sigma$

| POI category | Time slot | #POI | Bike usage per POI ($\times 10^3$) | Ratios $\bar{U}_a$ | $\bar{U}_b$ | $\bar{U}_c$ | $U_b/U_a$ (%) | $U_c/U_a$ (%) |
|--------------|-----------|------|-----------------------------------|-------------------|------------|------------|----------------|----------------|
| IRA          | All day   | 14   | 5.86 ± 2.95 1.50 ± 0.82 2.34 ± 0.30 | 25.50 | 39.90 |
| SRA          | All day   | 169  | 34.28 ± 17.32 8.30 ± 4.77 13.38 ± 1.33 | 24.20 | 39.00 |
| RA           | All day   | 5,657| 254.39 ± 133.76 61.65 ± 35.18 99.30 ± 5.59 | 24.20 | 39.00 |
sub-categories of RAs to assess the impact of confirmed cases, with results in Table 7. The IRAs and the surrounding RAs (SRA and the RAs surrounding IRAs) are surprisingly not the most affected category, implying that residents were in panic indifferently and limited their trips to basic needs. Based on the ratio $\frac{U_c}{U_a}$, the shared-bike usage of IRAs (39.9%) and their SRAs (39.0%) recovered roughly to the same level as other RAs (39.0%) from the pandemic.

6 | CONCLUSIONS

The widespread BSS is an alternative data source for characterizing the spatial and temporal details of human mobility. This article’s objective is to extract and analyze the impact of the pandemic on human mobility and the rehabilitation process at city scale. The results reveal the period-wise spatiotemporal characteristics and co-location patterns of human mobility presented by shared-bike usage before and during the pandemic in Beijing, China. Based on our analysis, we draw the following conclusions:

1. Apart from the timeline of the outbreak, we identified two key time nodes: January 23 and February 24, and segmented the study period (2 months) into three pandemic phases: phase a, before the pandemic; phase b, during the pandemic; phase c, when the pandemic was mitigated.

2. We used the DID model to assess quantitatively the net impact of the pandemic on various aspects of daily life. This simple but effective configuration (we considered only pandemic weather and holidays) suggests that the effect of the pandemic was important enough to overwhelm other candidate factors. After eliminating the factors of Chinese New Year holiday and weather, our results confirmed that the activities of residents were hugely affected by the COVID-19 pandemic, reflected in the drastic decrease in shared-bike usage (by 64.8%). Reductions in mobility close to subway stations (77.91%), high-tech companies (74.21%), and shopping plazas (73.58%) were higher than for other POI categories, which could be attributed to the quarantine restrictions and “work from home” message. Residential areas, supermarkets, and tertiary hospitals were less impacted, since people need basic food supplies and healthcare facilities.

3. With the mitigation of the pandemic, an increase in human mobility was observed following February 24. The rehabilitation progress was assessed by a category-wise co-location analysis. The average increase in shared-bike usage among the seven chosen POI categories is 15.9%, suggesting that mobility belonging to these types of functional areas had recovered to some extent, but was far from the situation of normal times following partial restart. The increase of 18.2% for high-tech companies and 17.6% for ordinary companies was higher than for other categories.

4. In addition, our results imply that the infected residential areas and other residential areas were not the most affected POI categories, and these two categories had recovered approximately to the same level (about 39.0%) from the pandemic.

The present case study was implemented in Beijing, a typical metropolis affected by COVID-19, excluding the epidemic center. As the situation develops globally, our results could be a generalized reference for epidemiological research and policymaking in the context of the current COVID-19 outbreak, and could be helpful for planning pandemic emergency response in the future.

7 | FUTURE WORK

Since the municipal government implemented multiple interventions simultaneously or in a short time frame to control the outbreak, the effect of individual strategies could not be evaluated. Multi-dimensional principal component analysis could be helpful in extracting the modes contributed by each preventive measure.
Additionally, our current work has extracted the features of mobility from BSS and POIs. Another possible extension is to build a dynamic model based on features predicting shared-bike usage and potential social events/reactions of the public during a pandemic or emergency.

ACKNOWLEDGMENTS
This study was supported by the National Key R&D Program of China (Grants No. 2018YFB2100701), the Research Program of Beijing Advanced Innovation Center for Future Urban Design (Grant No. UDC2019031321), the Pyramid Talent Training Project of Beijing University of Civil Engineering and Architecture (Grant No. JDYC20200322), and the National Natural Science Foundation of China (Grant No. 41601389).

CONFLICT OF INTEREST
The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT
The shared-bike data obtained from BeiDou Navigation & LBS (Beijing) Co., Ltd for this study are not publicly available due to stringent licensing agreements, but information on the process of requesting access to the data that supports the findings of this study is available from the corresponding author.

ORCID
Xinwei Chai https://orcid.org/0000-0001-7546-7068
Xian Guo https://orcid.org/0000-0003-0084-381X

ENDNOTE
1 Tertiary hospitals are considered the top-class hospitals in China.

REFERENCES
Ai, Y., Li, Z., Gan, M., Zhang, Y., Yu, D., Chen, W., & Ju, Y. (2019). A deep learning approach on short-term spatiotemporal distribution forecasting of dockless bike-sharing system. *Neural Computing and Applications*, 31(5), 1665–1677. https://doi.org/10.1007/s00521-018-3470-9
Akter, S., & Wamba, S. F. (2019). Big data and disaster management: A systematic review and agenda for future research. *Annals of Operations Research*, 283, 939–959. https://doi.org/10.1007/s10479-017-2584-2
Boulos, M. N. K., & Geraghty, E. M. (2020). Geographical tracking and mapping of coronavirus disease COVID-19/severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) epidemic and associated events around the world: How 21st century GIS technologies are supporting the global fight against outbreaks and epidemics. *International Journal of Health Geographics*, 19(1), 8. https://doi.org/10.1186/s12942-020-00202-8
Card, D., & Krueger, A. B. (1994). Minimum wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania. *The American Economic Review*, 84(4), 772–793. https://doi.org/10.3386/w4509
Chang, M.-C., Kahn, R., Li, Y.-A., Lee, C.-S., Buckee, C. O., & Chang, H. H. (2021). Variation in human mobility and its impact on the risk of future COVID-19 outbreaks in Taiwan. *BMC Public Health*, 21(1), 1–10. https://doi.org/10.1186/s12889-021-10260-7
Chen, L., Zhang, D., Wang, L., Yang, D., Ma, X., Li, S., ... Jakubowicz, J. (2016). Dynamic cluster-based over-demand 514 prediction in bike sharing systems. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, Heidelberg, Germany (pp. 841–852). New York, NY: ACM.
Chen, Z., van Lierop, D., & Ettema, D. (2020). Exploring dockless bikeshare usage: A case study of Beijing, China. *Sustainability*, 12(3), 1238. https://doi.org/10.3390/su12031238
Chinazzi, M., Davis, J. T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., ... Vespignani, A. (2020). The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science*, 368(6489), 395–400. https://doi.org/10.1126/science.aba9757
Du, M., & Cheng, L. (2018). Better understanding the characteristics and influential factors of different travel patterns in free-floating bike sharing: Evidence from Nanjing, China. *Sustainability*, 10(4), 1244. https://doi.org/10.3390/su10041244
Zhou, Y., Xu, R., Hu, D., Yue, Y., Li, Q., & Xia, J. (2020). Effects of human mobility restrictions on the spread of COVID-19 in Shenzhen, China: A modelling study using mobile phone data. The Lancet Digital Health, 2(8), e417–e424. https://doi.org/10.1016/S2589-7500(20)30165-5

SUPPORTING INFORMATION
Additional supporting information may be found online in the Supporting Information section.

How to cite this article: Chai, X., Guo, X., Xiao, J., & Jiang, J. (2021). Analysis of spatiotemporal mobility of shared-bike usage during COVID-19 pandemic in Beijing. Transactions in GIS, 25, 2866–2887. https://doi.org/10.1111/tgis.12784

APPENDIX

CALCULATION OF NET PANDEMIC EFFECT
From Equation (1), in the pandemic phase, Before$_{2020} = 0$, During$_{2020} = 1$, we have

\[ U = \exp(\alpha + \theta_1 + \epsilon_1) \cdot \exp(\beta_2) \]  \hspace{1cm} (A1)

Let \( \exp(\alpha + \theta_1 + \epsilon_1) = C \), and we have \( U = C \cdot \exp(\beta_2) \). The proportion of shared-bike usage reduction due to the pandemic effect is

\[ \frac{C - U}{C} = 1 - \exp(\beta_2) \]  \hspace{1cm} (A2)

See Figure A1 for corresponding graphs.
**FIGURE A1** POI-wise evolution of shared-bike usage