Analysis of Spatial-temporal Behavior Pattern of the Share Bike Usage during COVID-19 Pandemic in Beijing

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Abstract: During the epidemics of COVID-19, the whole world is experiencing a serious crisis on public health and the economy. Understanding the behavior of residents during epidemic benefits emergency management when one tries to design intervention strategies and resilience measures. From the perspective of movements, the widely used Bike Sharing System (BSS) in China is capable of characterizing the behavior patterns over time & space within big cities. Although share bikes are playing an important role as data sources in data mining, they could be of help but are rarely reported in pandemic-related researches. Based on the share bike records in Beijing, we constructed a behavior pattern analysis framework, then analyzed the spatiotemporal behavior patterns of residents, figured out the key time nodes of different pandemic periods, and demonstrated the variations in mobility due to the onset of the COVID-19 threat and administrative restrictions. The impact of the pandemic was assessed by performing co-location analysis between share bike usage and POIs (Point Of Interest). Classification of POIs is helpful to distinguish the behavior patterns generated by various productive and social activities. Discussions with evolving confirmed COVID-19 cases suggest the effectiveness and necessity of the public interventions in the COVID-19 containment during the resilience period. These findings provide critical information on how to respond to the current COVID-19 outbreak and other epidemic events.

Keywords: Bike sharing system; COVID-19; spatiotemporal analysis; behavior pattern; co-location analysis

1. Introduction

COVID-19 is a rapidly spreading infectious disease caused by the novel coronavirus SARS-COV-2, which has now established a global pandemic. According to a situation report of WHO, the worldwide total confirmed cases have reached 2,471,136 including 84,287 that of China as of 22 April 2020. It is well-accepted that COVID-19 pandemic inflicts a huge impact on public health and most of the domains of economy, from the Chinese New Year holiday till today (April 2020).

References:
1 https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it
2 https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200422-sitrep-93-covid-19.pdf
Under the threat of the pandemic, the activities of residents are inevitably influenced and restricted. Since it is associated with productive and social activities, the behavior of residents is used as one of the evaluation indicators for post-disaster reconstruction [1,2]. Measuring the changes in the behavior of residents is urgent to enhance emergency management and post-disaster recovery of the current COVID-19 outbreak. Current COVID-19-related epidemiological studies mainly focus on transmission dynamics [3,4] and preventive measures [5,6] based on the timeline of outbreak. However, few studies have been reported to analyze quantitatively the spatiotemporal patterns of public behavior during pandemic situations, which is essential for planning preventive strategies and impact assessments on the economy and society. Ferguson et al. [7] have studied two main strategies in the prevention of infectious diseases: suppression, case of China and South Korea, with enormous social and economic costs which may cause secondary disasters on health and well-being in the short and longer-term; mitigation, case of Great Britain and the United States, may not be able to deal with all those with severe disease and resulting in high mortality. Available studies on human mobility patterns during disasters mainly focus on short-term emergencies (e.g., fires, and earthquakes) [8,9]. Research on the dynamics of the behavior of residents on a detailed scale during a long-term pandemic is very limited.

The emergence of geospatial big data has great potential to benefit the applications in disease surveillance and disaster response in the past [10–12]. Horanont et al. [13] made use of mobile phone data collected after the 2011 Great Japan Earthquake and provided useful information on how humans react in disaster scenarios and how the evacuation process can be monitored. After the 2015 Nepal Earthquake, Wilson et al. [14] used call detail records about phone metadata tracking numbers and times of calls to estimate population distribution and socioeconomic status for risk assessment. With geotagged social media data, Chae et al. [15] conducted comprehensive research in spatiotemporal analysis and created a spatial decision support environment that assists in evacuation planning and disaster management. Wesolowski et al. [16] used spatially explicit mobile phone data and malaria prevalence information from Kenya to identify the dynamics of human carriers that drive parasite importation between regions. In this paper, we focus on the spatiotemporal patterns of public behavior response to the COVID-19 pandemic in Beijing, China. To achieve this goal, VGI (Volunteered Geographical Information) plays an important role, in which online surveys and mobile phone positioning data could be references, but they do not cover all the population especially those who care about their privacy and are not willing to offer their precise position [17].

Wide-spread Bike Sharing System (BSS) in China provides a possibility for analyzing such patterns of residents. The 3rd generation BSS (free-floating BSS) emerges in China in 2015 thanks to the rapid development of GIS-based and IoT-based system. Compared to its predecessors, bikes of the 3rd generation BSS (hereinafter referred to as BSS) are no longer constrained by docking stations (so-called free-floating bikes). They are often spread along the roads, congest around shopping/residential areas (RAs), and cover most of the urban residents. As for the city of Beijing, the number of share bikes reached its peak in 2017 and the governors began removing the excess supply afterward. After two years of rapid development and optimization of BSS, the demand and the supply of share bikes meet a balance in 2019, which could be regarded as a stable data source. BSS records contain time and location information of bike usages from anonymous users, providing a valuable indicator of human presence, thus offering a promising alternative data source for increasing the spatial and temporal detail of the mobility and the activities of residents during the pandemic. According to Daxue Consulting [18], in Beijing, 93% of travels less than 5km are quicker done by bike and public transport than with the car, which suggests share bikes have a potential reflection on the local mobility of residents.

The activities of residents in various regions can be easily captured with BSS data, and be used to address the issues such as traffic planning, urban vitality assessment. Du et al. [19] studied the travel patterns of BSS in Nanjing via limited questionnaires. Xu et al. [20] characterized the share bike temporal
flow and spatial distribution in Singapore. Kaggle organized a competition of predicting share bike demands\(^3\) based on limited entries. There are also studies of BSS focusing on rebalancing strategies [21–23]. While BSS data analytics has been successfully applied in many sectors, their application in pandemic response is still at its early stages. Moreover, due to limited emerging understanding of the new virus and its transmission mechanism, revealing its impacts on public behavior remains challenging. As far as we know, there is no study on the impact of social events and/or emergencies based on the 3rd generation BSS.

In this study, we constructed a behavior pattern analysis framework based on share bike usage to measure period-wise spatiotemporal behavior patterns of residents in Beijing. As preconditioning, a comparison between the same period of 2019 and 2020 was conducted to remove the effect of the Chinese New Year holiday. Identification of the key time nodes in different pandemic periods was conducted by segmenting the whole time series while keeping the maximal similarity inside the segments. In different pandemic periods, we implemented a co-location analysis between the usage patterns and different types of POIs, which reveals the public reactions and assess the impact of the COVID-19 pandemic. Finally, we analyzed the relevance between the change of behavior patterns and the progress of confirmed cases, and assess the effectiveness of suppression strategies. The main novelty of our proposed work is to depict public responses to the progress of COVID-19 from spatiotemporal perspective by interpreting the behavior patterns of residents extracted from long time-sequenced share bike records. Therefore, the impact of the COVID-19 pandemic and the influence of suppression strategy could be analyzed on a citywide scale, providing references in more detail for policy-making and epidemiology research.

The remainder of this paper is organized as follows. Section 2 & 3 describe the study area and proposed methods. Section 4 reports the spatiotemporal change in behavior patterns regarding the local COVID-9 progress and co-location analysis with POIs. Discussions are presented in Section 5 in comparison with the previous year, and relation with confirmed cases during different pandemic periods. Section 6 concludes with some remarks and Section 7 hints future research lines.

2. Study Areas 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 locates at the North China Plain, occupying an area of 16,411km\(^2\) (39.4°-41.6°N, 115.7°-117.4°E). In 2019, the municipal population of Beijing has reached 21.53 million. According to the Beijing Health Commission, the COVID-19 confirmed cases\(^4\) bring the cumulative total in Beijing to 418 by 05 Mar 2020. As a population-importing metropolis, Beijing has taken several efforts in response to the outbreak. Under this circumstance, the activities of residents have been influenced and showing special spatiotemporal patterns different from ordinary days.

2.2. Description of Data Sets

Before describing our results in spatiotemporal patterns of share bike usage, it is first important to introduce data sets adopted in our experiments.

**BSS spatiotemporal data** Temporal positioning datasets come from 1.02 million share bikes belonging to 4 main BSS operators (Mobike, DiDi Bike, Hellobike, and Ofo) in Beijing. The datasets date from March

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\(^3\) https://www.kaggle.com/c/bike-sharing-demand
\(^4\) http://wjw.beijing.gov.cn/xwzx_20031/wxxw/202003/t20200305_1679143.html (in Chinese)
2019 to March 2020 (66.8 GB) and cover 1.5 million uses per day contributed by 11 million users which account for one half of the total population of Beijing. Records of the datasets contain the positioning and timing information of locking & unlocking of bikes, excluding that of rebalancing operations. This feature suggests that the movement of bikes is purely done by users. All analysis we perform is statistically aggregated, removing the ability to characterize the behavior of any single device. Certain districts (Chaoyang, Fengtai, and Shijingshan) are not comprised in the datasets due to different policies of local governments.

Points Of Interest (POIs) POIs of Beijing are collected from AutoNavi API. Each entry is identified by object_id, recording the address including longitude/latitude information, and categorized by large_category, mid_category and sub_category. Among hundreds of categories, we chose six mid ones characterizing productive and social activities: residential area (RA), tech company, other company, subway station, shopping plaza and supermarket.

Locations of Confirmed Cases The daily cumulative counts of clinically diagnosed cases subjected to each district from Jan 20 to Mar 5, 2020, were collected from the daily update on the novel coronavirus pneumonia outbreak dashboard provided by National Health Commission of the People’s Republic of China. According to the timeline of the outbreak, we picked several important dates shown in Figure 2, visualizing the evolution of the overall pandemic situation of Beijing. To assess the overall behavior pattern changes, we picked out the locations of a total of 87 infected RAs (see Figure 3), which were retrieved from Beijing Municipal Health Commission.

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5 https://lbs.amap.com/api/webservice/guide/api/georegeo (in Chinese)
6 http://www.nhc.gov.cn/xcs/yqtb/list_gzbd.shtml (in Chinese)
7 http://wjw.beijing.gov.cn/xwzx_20031/xwxw/202003/120200305_1679143.html (as of March 05, 2020, in Chinese)
3. Methodology

Figure 4 shows the workflow of our study to assess the reactions of residents to COVID-19 by the above data sets. To deal with large-scale spatial queries of the huge amount of BSS spatiotemporal data (66.8GB), we made use of parallel computing all along the two main threads:

1. GeoSpark [24] acts as an engine processing co-location analysis of POI and BSS data, and the result is aggregated and visualized by ArcGIS in the form of heatmaps. This thread is designed to quantify the spatial relationships between POIs and share bike usage. Details will be given in Section 3.1.
2. Spark SQL8 is used to process temporal queries in BSS data then obtain mean, and standard error. This thread is to identify key time nodes based on the changes of share bike usage corresponding to COVID-19 and explore the temporal characteristics of share bike usage. Details will be given in Section 3.2. A next-step process (visualization and optimization) is done in Python.

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8 https://spark.apache.org/
Geographic visualization is supported by ESRI ArcGIS 10.7. By synthesizing the results above, we managed to reveal behavior patterns of share bike usage during the pandemic.

![Diagram](https://example.com/diagram.png)

**Figure 4.** Overview of the proposed behavior pattern mining workflow

### 3.1. Co-location Analysis

To obtain the co-location patterns in such datasets with numerous POIs, we proceeded with GeoSpark, which allows spatial queries via parallel computing on cluster computing framework Spark. Among the spatial queries, we utilized `spatial_join(geom1, geom2)`, querying if object `geom1` is inside `geom2` and `distance_join(geom1, geom2, dist)` querying if the distance of `geom1` and `geom2` is less than `dist`. These queries are nearly partition-independent, recomputing is needed only on the borders of partition, thus our parallel efficiency is high given proper configuration and partitioning.

### 3.2. Phase Classification

In the domain of machine learning, it is often demanded to minimize the predefined loss function to perform the best classification such that elements within the same cluster are similar and elements across clusters are different. Likewise, we try to segment the study period into phases that have the most resembling 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 positive integer $k < N$ 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 $0 \leq i \leq k - 1$.

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9 [https://www.esri.com/en-us/arcgis/about-arcgis/overview](https://www.esri.com/en-us/arcgis/about-arcgis/overview)
To evaluate the quality of k-segmentation, we use $\sigma = \sum_{i=1}^{k} \sigma_i$ as 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 is solved in time $O(N^2k)$ [25]. In case $k$ and $N$ are small, the optimum can be found via exhaustive search.

4. Experimental results

The computation in this paper was done on a computing cluster consisting of 5 machines with Intel(R) Xeon(R), CPU E5-2640 v2 @2.00GHz, 8 cores, 61.7GB memory, 20480KB cache memory. If we throw a first glance on the total share bike usage from 01 Jan to 02 Mar, which is $4.56 \times 10^7$ in 2019 and $1.61 \times 10^7$ in 2020 we found out the total of 2020 is about only one-third of that of 2019 in this period.

In this section, we present extensive experimental results of the spatiotemporal change in behavior patterns regarding the local COVID-9 progress and the association with POIs.

4.1. Temporal Patterns of Share Bike Usage

To better characterize the behavior patterns with respect to the COVID-19 epidemic dynamics, we first selected the following important referential dates in Table 1 that could affect the virus transmission in Beijing:

| Date       | Event                                      |
|------------|--------------------------------------------|
| 04 Feb 2019| Start of Chinese New Year holiday 2019     |
| 10 Feb 2019| End of new year holiday 2019              |
| 07 Jan 2020| Identification of COVID-19                |
| 22 Jan 2020| Shut down of Wuhan and other 15 cities   |
| 24 Jan 2020| Start of Chinese New Year holiday 2020   |
| 02 Feb 2020| End of extended New Year holiday 2020     |
| 10 Feb 2020| Partial restart of productive and social activities |

Table 1. Important dates

As the outbreak of COVID-19 coincides with the Chinese New Year holiday 2020, we use the Chinese New Year holiday of 2019 as a comparison to assess the influence of this period on share bike usage. It is worth noticing that the Chinese New Year holidays are not equal-length, because that of 2020 is extended by executive order.

We compared the share bike usage on rush hours (8:00-09:00) during 64 days from 01 Jan to 02 Mar 2019 and 01 Jan to 01 Mar 2020 respectively (data of 29 Feb and 1 March 2020 were brought backward by one day due to the leap year 2020).

Figure 5 illustrates the temporal evolution of share bike usage.

The share bike usage drops in mid-January of 2020 and early February of 2019. During these periods, schools and workplaces were closed as part of the Chinese New Year holiday 2020. The overall closure was then forced to be extended to mitigate the pandemic.

Share bike usage on rush hours exhibits the periodicity of productive activities: high on weekdays and low on weekends, which fits our general knowledge. However, this pattern does not appear on 10 Feb 2020 when the government declared the partial restart of certain productive and social activities. This anomaly suggests that the activities were not resumed at all at least until Feb 17, one week after the partial restart, corresponding to the fact that the impact of the pandemic was lasting till the end of our study period.

Table 2 gives a rough quantitative view over the impact of the pandemic.

Note: In this paper, we consider share bike usage follows normal distribution, of which 95% confidence interval is $[\bar{x} - 2\sigma, \bar{x} + 2\sigma]$. Share bike usage data are presented in the form $\bar{x} \pm 2\sigma$.

The upper part shows that in the rush hours of ordinary days, share bike usage in 2020 is on the same level as that of 2019, suggesting share bike demand is evolving smoothly. However, the lower part
shows the case of the Chinese New Year holiday, the overall share bike usage drops to less than 40% compared with the same period in 2019, suggesting companies stopped working due to the Chinese New Year holiday like the case of 2019, and social activities also halted.

According to Figure 5, it is implied the dates in Table 1 may not be the optimal boundaries of different phases, as there is no obvious share bike usage change after Feb 10.

We obtained a time series by computing the share bike usage within 200m of each POI every day in the period 02 Jan to 02 Mar 2020. Then we segmented the time series into three phases using Definition 1 in Section 3.2. Here \( k = 3 \) and \( N = 62 \), we found the best-classified phases with the minimum sum of standard deviation using exhaustive search. According to the result in Table 3, these phases can be identified as: before pandemics (Phase a), during pandemics (Phase b), pandemics mitigated (Phase c).

| Category               | Split point 1 | Split point 2 |
|-----------------------|---------------|---------------|
| Tech company          | 23 Jan        | 24 Feb        |
| Other company         | 23 Jan        | 28 Feb        |
| RA                    | 24 Jan        | 24 Feb        |
| Subway station        | 24 Jan        | 24 Feb        |
| Shopping plaza        | 24 Jan        | 24 Feb        |
| Supermarket           | 24 Jan        | 24 Feb        |
| Overall               | 23 Jan        | 24 Feb        |

Table 3. Period segmentation of 02 Jan to 02 Mar 2020

| Phase                      | Daily average share bike usage (10^5) |
|----------------------------|----------------------------------------|
|                           | 08:00-09:00 (on weekdays)  | 18:00-19:00 (on weekdays)   | All-day   |
| 02 Jan-20 Jan 2019        | 2.46 ± 0.59                  | 1.30 ± 0.39                  | 15.0 ± 4.5   |
| 02 Jan-20 Jan 2020        | 2.58 ± 1.10                  | 1.37 ± 0.74                  | 12.7 ± 6.3   |
|                           | 08:00-09:00 (all week)       | 18:00-19:00 (all week)       | All-day    |
| 04 Feb-10 Feb 2019        | 0.30 ± 0.05                  | 0.24 ± 0.08                  | 4.90 ± 1.56  |
| 24 Jan-02 Feb 2020        | 0.10 ± 0.02                  | 0.12 ± 0.03                  | 1.72 ± 0.35  |

Table 2. Overall comparison of year 2019 and 2020.
A minor difference between the share bikes near companies and those near living facilities can be explained by a lag between the end of work and the start of vacation. Social and productive activities have not resumed until 24 Feb which is two weeks after the declaration of the partial restart. The companies except for tech companies correspond mostly to the real economy are delayed another one week.

4.2. Spatiotemporal Patterns of Share Bike Usage

Figure 6 shows the spatial patterns of BSS activities from 21 Jan to 02 Mar by 4-day intervals, which is consistent with the changes detected in Figure 5. The daily share bike records are aggregated within 500-meter grids and rendered with a color ramp from grey to green to red (as is in Legend).

Before 21 Jan 2020, share bike activities were widely distributed throughout the city limits, with a significant concentration in the downtown area, which is orange or even red, corresponding to high-intensity activities (up to 500-1000 records/hour). These patterns could be regarded as a comprehensive reflection of the activities of the individuals in these regions and used as a reference to compare with that during the COVID-19 pandemic.

After the COVID-19 outbreak, there is a dramatic drop in mobility since 25 Jan, which was also the beginning of the Chinese New Year holidays. High-intensity activities could hardly be recognized in the subfigures between 25 Jan to 02 Feb. These subfigures are dominated by green and light green
corresponding to low-intensity activities (<100 records/hour), indicating that individuals have demands to go out during this period, but unnecessary going-out has been significantly reduced by the combined effects of holidays and the epidemic. Status continued until 09 Feb, when the spread of COVID-19 was slowed down by imposing control measures including social distancing and home quarantine, and productive and social activities were allowed to restart partially.

Figure 6(f)-6(k) from 10 Feb to 01 Mar 2020, show a gradual increase in the mobility of the share bikes, but only restored around 30% of the pre-epidemic levels. As consistent with the Figure 5, there is a fluctuation near 14 Feb due to the increase in confirmed cases, which will be discussed in Section 5.2. It is worth noticing that only slight differences could be observed between weekdays and weekends before 17 Feb and the weekday-weekend oscillation returned afterward.

There is a higher demand for share bikes on workdays in the downtown area than before. However, the high-intensity areas shrank on weekends, implying that residents were more inclined to reduce the risk of increased exposure by going outside under the threat of COVID-19.

The spatiotemporal analysis above verifies the segmentation of the outbreak timeline into 3 phases in Table 3.

4.3. Co-location Analysis with POIs

It is beneficial for pandemic management to acquire information on human activities in different urban zones. Intuitively, the number of share bike records implicitly reflects the human activities of a certain place. Consequently, to assess the spatial distribution of share bike usage near various categories of POIs, buffer zones centered on each POI, with a range of 200 meters, were established to accumulate the share bike usage that fell in the area. We then computed the average share bike usage in these phases respectively. Results are reported in Table 4. In the table, a, b and c stand for share bike usage during phase a, b, and c for simplicity. Beside them, two ratios are used to measure the extent to which the COVID-19 epidemic has led to the decline in various activities. Ratio b/a describes the decline in share bike usage during the quarantine period, and the recovery status can be inferred from ratio c/a when the pandemic mitigated.

| Category          | POI amount | Daily average bike usage within 200m radius of POIs per POI | a    | b    | c    | b/a  | c/a  |
|-------------------|------------|-------------------------------------------------------------|------|------|------|------|------|
| Tech company      | 3858       | 200.4 ± 112.9                                              | 36.3 | 14.4 | 41.1 | 18.1 | 20.5 |
| Other company     | 32301      | 162.5 ± 90.3                                               | 35.8 | 14.5 | 39.4 | 22.0 | 24.2 |
| RA                | 5657       | 158.3 ± 86.9                                               | 36.6 | 14.4 | 39.9 | 23.1 | 25.2 |
| Subway station    | 137        | 138 ± 66.6                                                 | 29.0 | 11.8 | 31.7 | 25.5 | 27.9 |
| Shopping plaza    | 217        | 168.9 ± 91.7                                               | 38.4 | 14.6 | 41.0 | 22.7 | 24.3 |
| Supermarket & grocery | 1076    | 137.6 ± 76.0                                               | 34.3 | 13.4 | 37.7 | 24.9 | 27.4 |

Table 4. Bike usage in different phases around the chosen POIs.

Table 4 depicts the bike usage of the six chosen categories. Ratio b/a shows that the bike usage of all categories decreased to one quarter, and tech companies dropped the most in both values (from 200.4 in a to 36.3 in b) and proportion (18.1%), one possible explanation is they suit best “work from home”. During this period, the intensive intracity public traffic (e.g., buses) was limited to avoid contact infection, and share bikes became feasible vehicles to fulfill short-term travel demand under this situation. This ratio of the subway station (25.5%) and supermarket & grocery (24.9%) are higher than in other categories. One possible reason for this phenomenon is the need for the residents to procure essential goods, though outdoor activities were voluntarily reduced during the quarantine.

Ratio c/a shows the bike usage of all categories has recovered to some extent but far from the situation of usual time after the partial restart of activities. The average increase of the six chosen categories is 2.2%
when compared with Phase b, and their recovery progress differs from each other. The shopping plazas yields the lowest increase rate at 1.6%, which could be attributed to distancing restrictions for personnel dense places. Partial resumption of work leads to a slight increase in the daily average share bike usage near two company categories, with 41.1 for tech companies and 39.4 for other companies. Ratio $c/a$ being 20.5% and 24.2% suggest there is still a while from full recovery. During the mitigation period, subway stations and supermarkets serving as the main public transportation and subsistence suppliers, remain the highest level of recovery, with the ratio $c/a$ up to 27.9% and 27.4%.

To visualize the above differences in spatial patterns over pandemic phases, Figure 7-10 take the results of 16 Jan, 15 Feb, and 2 Mar as profiles of Phase a, b and c, and show the map with position of our selected categories of POIs and the share bike usage within 500$m \times 500$m grids.

As can be inferred from Figure 7 and Figure 8, metro stations, and malls always position in the center of massive share bike clusters. In Figure 9, tech companies are crowded in the northwest of Beijing which takes the biggest share bike usage. Although a drastic decrease in share bike usage can be observed during the quarantine period, some share bike usage remained around metro stations and malls, which is consistent with Table 4.

According to figures corresponding to 2 Mar, mobility is recovering after the pandemic was mitigated. Share bike usage of relatively high intensity can be found located in the area adjacent to the subways station in 7(c). It should also be figured in 9(c) that the use of share bikes is on the rise and has a strong correlation with the spatial distribution of the company.
From Figure 3, we noticed that being the center of Beijing, Dongcheng and Xicheng district contain most of the infected RAs, and the confirmed time lies between 05 and 12 February. Like in Section 4.3, we adjusted the time intervals to match the confirmed time and carried the same analysis on the share bike usage around infected RAs and that of surrounding RAs (within the range of 1500m of infected RAs).

| Category          | RA amount | Daily average bike usage within 200m radius of RAs per RA |
|-------------------|-----------|-----------------------------------------------------------|
|                   |           | 01 Jan-21 Jan (a) | 05 Feb-12 Feb (b) | 13 Feb-04 Mar (c) | b/a | c/a |
| Infected RA       | 19        | 160.8 ± 39.4     | 27.3 ± 22.7      | 43.2 ± 32.6      | 17.0%| 26.9%|
| Surrounding RA    | 1591      | 139.2 ± 84.4     | 26.8 ± 20.1      | 38.7 ± 26.1      | 19.3%| 27.8%|
| All RA            | 5657      | 158.3 ± 86.9     | 36.6 ± 14.4      | 39.9 ± 13.9      | 23.1%| 25.2%|

Table 5. Bike usage in different phases of infected RAs and that of surrounding RAs.

From Table 5, it can be inferred that the infected RAs suffered the most among the listed categories according to ratio b/a. Strict quarantine was practiced here to mitigate the pandemic. Surrounding RAs were also strongly impacted because of the residents got into a panic and keep themselves at home. According to ratio c/a, the share bike usage of infected RAs and their surrounding RAs have recovered roughly to the same level compared to other RAs from the pandemic.

As can be seen from the share bike usage of 16 Jan in Figure 10, the infected RAs are situated in the city center, with a huge pedestrian flow rate surrounded by massive share bikes. On 15 Feb, there is nearly no share bike usage around these infected RAs. On 2 Mar, share bike usage recovery can be observed in many regions, but the increase is not obvious around the infected RAs, unlike metro stations and shopping plazas.
We can conclude the residents in Beijing followed exactly the suppression strategy whether the RAs were infected or not: quarantine, *cordon sanitaire*, and social distancing.

5. Discussions

In this section, we first compare bike usage of 2019 and 2020, to demonstrate the influence of pandemic in resident activities apart from the impact of holiday. Associated with the distribution of confirmed cases, the variations of behavior patterns are interpreted concerning different pandemic periods subsequently.

5.1. Comparison between 2019 and 2020

Both Chinese New Year holiday shutdowns and pandemic resulted in the aforementioned mobility decrease. Therefore, a comparison was conducted with data from the same period in 2019, thus removing the impact of the Chinese New Year holiday and evaluating the specific influence of the pandemic. The average values of aggregated daily share bike records from each pandemic phase were reported.

Figure 11 delineate the share bike usage in *phase a,b,c* of 2020, that in corresponding period of 2019, and the difference in between. Figure 11(a)-11(c) were consistent with the daily patterns during different pandemic stages presented in the previous section. Figure 11(d) summarized the averaged share bike usage intensity during the same time-interval as *phase a* in 2019, showing similar spatial patterns as 2020. Comparable numbers of positive and negative area could be observed from annual difference presented in Figure 11(g). These discrepancies have relatively low values which could be attributed to the fluctuation of regional bike usage requirements.

The significant discrepancies in share bike usage between the year 2019 and 2020 during *phase b* and *phase c* is considered as the consequence of the pandemic of COVID-19. Normally, most migrants (34.6% of the population of Beijing) go back to their hometown during the Chinese New Year holiday; while permanent residents enjoy family gatherings and the main outdoor activity is visiting relatives and friends. Therefore the holiday shutdowns reduced mobility in 2019, but high-intensity mobility could still be found in the urban districts from Figure 11(e). Correspondingly, activities were in a state of complete suppression in 2020. The difference map in Figure 11(h) reveals the fact that under the impact of COVID-19, demands for outings were reduced for safety purposes.

In previous years, Figure 11(f) indicated that mobility would instantly return to pre-festival levels or more widespread as a result of the influx of migrant workers after the holiday. According to Figure 11(c), the rehabilitation was in progress, but much slower during the epidemic mitigated period. The remarkable difference referred from Figure 11(i) verified this sustained impact on the daily lives of citizens.

5.2. Relationships between Share Bike Usage and Confirmed Cases during Pandemic Periods

This part aims at characterizing the variations of behavior patterns by evaluating share bike usage concerning different pandemic periods. Figure 12 shows the share bike usage in *phase b*, i.e., the quarantine period. Same as previous sections, aggregated share bike records were rendered with a color ramp from grey to green to red. Confirmed cases in each district are displayed by blue circles, where the cumulative number of cases is shown by the size of circles. When comparing the panels from left to right with the date varying from 25 Jan to 08 Feb, we observe that the aggregated share bike intensity gradually decreases with an increasing number of confirmed cases and then remains at a low level. The aggregated share bike intensity in the downtown area changed from red to green. Starting on January 25, 2020, highly restrictive measures were implemented by local government: individuals were asked to follow a series of social distancing measures. As a result, the number of newly confirmed COVID-19 cases was effectively suppressed.
Figure 11. Comparison of share bikes usage between 2019 and 2020 in different pandemic periods.

Figure 13 depicts the share bike usage in **phase c**, when productive and social activities were allowed to restart partially.

During this mitigation phase, share bike usage was gradually rebounding with stable accumulated confirmed cases during the weekdays, which can be inferred from Figure 13(a)-Figure 13(e). The recovery of the city is unbalanced in the spatial domain, concentrating in urban districts, whereas changes are not significant in other areas. Another finding is the different patterns between weekdays and weekends. A reduction in mobility on weekends could be inferred from the comparison between Figure 13(e) and Figure 13(f), which was attributed to the awareness of the risk of infection of residents.

It should be highlighted that the accumulated confirmed cases stay substantially stable across this period, suggesting control measures were effective and necessary in the containment of the spread of COVID-19 during the resilience of Beijing.
6. Conclusion

The wide-spread BSS is an alternative data source for characterizing the spatial and temporal detail of the mobility and the activities of residents. Motivated by the current COVID-19 outbreak and rapid development in BSS, this paper constructs a framework targeting at extracting and analyzing behavior patterns based on long time-sequenced share bike usage.

Based on share bike usage, we investigated the impact of the pandemic on the behavior of residents and the rehabilitation process on the city scale. After removing the factor of the Chinese New Year holiday, our results suggest that social and productive activities of residents were hugely affected by the COVID-19, reflected in the drastic decrease of share bike usage (down to less than 40% of that of the same period in 2019). It can be figured out that the cumulative confirmed cases stayed stable substantially after the restarting of productive activities, implying the ongoing control measures were necessary and effective in the containment of the spread of COVID-19 when opening-up. Co-location analysis shows the infected RAs situated in the city center are most impacted, even after the pandemic is mitigated; Among POIs, share bike usage of tech companies has the biggest change before and during the pandemic as these companies are most suitable for “work from home”, etc. These findings provide supplementary details to the public reactions during the pandemic. As the situation develops globally, our results could be references to epidemiological researches and inform policymaking in the context of the current COVID-19 outbreak, and help to prevent the emergence of pandemics in the future.
7. Future Work

Since the government implemented multiple interventions at the same time or in a short timeframe to control the outbreak, individual strategies could not be evaluated. The multi-dimensional principal component analysis could be helpful to extract the modes contributed by each preventive measure.

Also, our current work has extracted the features of mobility reflected by BSS. Another possible extension is to build a dynamic model based on the features predicting the share bike usage and potential social event/reaction of the public during the pandemic or emergencies.

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Abbreviations
The following abbreviations are used in this manuscript:
BSS  Bike Sharing System
GIS  Geographic Information System
POI  Point Of Interest
RA  Residential Area
VGI  Volunteered Geographical Information

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