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A long-term perspective on the COVID-19: The bike sharing system resilience under the epidemic environment

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ABSTRACT

Introduction: The sudden COVID-19 pandemic poses a fresh and tough challenge to bike sharing systems (BSS). With this epidemic as a shock event, this paper aspires to shed light on the phenomenon of changing demand and usage regularity in New York City’s BSS under the epidemic environment, spanning a period of 18 months.

Methods: Technically, BSS’s normal performance and the timely responses to the outbreak could be conceptualized as having four different stages. One provides a comparative analysis of bike sharing spatial-temporal mobility patterns and connectivity of the bike sharing usage network, before and during the public health crisis with a macroscopic perspective. Also, a multivariate investigation of user and trip characteristics on BSS is conducted to uncover the difference in the frequency of outdoor and sojourn time between various user communities.

Results: Due to the impact of the outbreak, BSS registered severe ridership drops, yet it quickly recovered to the pre-pandemic levels within months. The decline of bike sharing usage was felt throughout all the areas during the outbreak. However, there were places where BSS ridership actually increased, particularly in the areas near supermarkets, parks and hospitals. The less densely connected network of the bike sharing usage has also resulted in a reduction in users’ destination heterogeneity. This study also finds evidence of the significant gender, age and cycling pattern gaps in response to potential risk.

Conclusions: Investigating the dynamics of bike sharing usage will help to comprehend how the serious pandemic caused by COVID-19 impacts people’s daily mobility. Practically, this work hopes to provide insights into adapting this unprecedented pandemic so as to respond to similar events in the future.

1. Introduction

Transport options that involve physical activity are referred to as active transport, such as cycling (Woodcock et al., 2021; Crist et al., 2021). It has wide-ranging individual and societal-level benefits. At its most straightforward, cycling contributes to maintaining and improving health and physical fitness. Strong evidence demonstrates that cycling behaviors have been associated with a reduction in chronic diseases, as well as increased cardiovascular and metabolic functions (Reilly et al., 2020; Crist et al., 2021). Apart from the...
substantial net health benefits, increased levels of cycling could further mitigate traffic congestion, decrease fuel consumption and air pollution, lower transportation cost, enhance environmental awareness, and facilitate the use of public transit (Barbour et al., 2019; Belanger-Gravel and Janezic, 2021). These population-level health benefits have also been recognized. In recent years governments have set cycling targets to encourage the use of active transport to improve health outcomes (Cheng et al., 2021; Woodcock et al., 2021).

Bike sharing systems (BSS) allow people’s short-term access to bicycles, when needed without bearing the cost and responsibilities of bike ownership (Chen et al., 2018; Bi et al., 2021). It has recently received large-scale acceptance as a low cost and health-inducing transportation option. Indeed, they offer an opportunity for active transport and have been shown to increase cycling (Bibagoli et al., 2019; Reilly et al., 2020; Wang and Zhou, 2017). However, unsteady urban transport networks can affect “normal” cycling behaviors, and result in the decrease of usage of bicycle and health benefits of cycling (Wu and Kim, 2020; Song et al., 2022). Along with other modes, a bike sharing system is vulnerable to various external factors (Eren and Uz, 2020; Kutela and Teng, 2019; Scott and Ciuro, 2019; Sun et al., 2018). Specifically, factors that cause short-term disruptions mostly pertain to facility maintenance (Usama et al., 2019), inclement weather conditions (Ashqar et al., 2019), social activities (e.g. strike and protest) (Fuller et al., 2019), and temporary policy (e.g. during festivals) (Kaplan et al., 2015). Long-term causes may be due to natural disasters, like earthquakes, tsunamis, and typhoons (Lu et al., 2019; Chikaraishi et al., 2020), as well as public health events, like SARS, H1N1, and the current COVID-19 pandemic (Nakamura and Managi, 2020; Chibwe et al., 2021). Before COVID-19, there were some studies that aimed to capture the influences of epidemic events on traditional transport modes (Cui et al., 2011; Zhang et al., 2011). As an alternative mode of transport with its advantage in social distancing, a shared bike serves as a lifeline to satisfy the daily mobility demand of people during the COVID-19 pandemic (Shokouhyar et al., 2021; Hua et al., 2021). However, it’s the first pandemic strike since the emergence of bike sharing systems.

The novel coronavirus (COVID-19) was identified in Wuhan, China; since then, the situation has evolved into a global pandemic (Iqabal et al., 2020). Countries have taken drastic measures to contain the spread through their nations. The outbreak of COVID-19 has posed unprecedented challenges for the US. The state of New York (NY) contained around 14% of the total cases and 24.5% of the total deaths nationwide by June 2020, and has become the epicenter of the outbreak, especially in New York City (NYC) (CNN, 2020a). Furthermore, NYC is one of the earliest cities that declared a State of Emergency, implementing a series of measures (CNN, 2020b). There has been an inevitable impact on the movement of New Yorkers among every traffic mode, which includes BSS. This paper aims to better understand and reveal the relationship between bike sharing usage regularity and the COVID-19 pandemic by examining the impact of the outbreak on the Citi Bike sharing system and mobility patterns in NYC.

This study does not deal with the epidemiological aspects of the current pandemic, instead focusing on estimates of long-term impacts of the COVID-19 pandemic within the bike sharing system itself over time. Thus, a brief review of the development of the COVID-19 pandemic in NYC is presented first, which is the basis of the following analysis. Then, this study conducts a spatial-temporal analysis of bike sharing usage patterns and a comparative network analysis of bike sharing demand networks in macro view. The combined spatial-temporal-statistical technique and the complex network approach adopted here bring insight into the evolution process of BSS. Furthermore, multivariate investigation of user and trip characteristics on bike sharing system is used to capture the difference in the frequency of outdoor and sojourn time between various user communities.

To that effect, the study is organized into the following sections: Section 2 presents a literature review on the impacts of external factors on bike sharing systems; Section 3 offers an introduction to the study area and data used in the study; Section 4 provides an overview of the development of the COVID-19 pandemic in NYC; Section 5 presents the results of analysis; while Section 6 summarizes the conclusions and recommendations.

2. Literature review

2.1. Impact of historical public health events on traffic

Before COVID-19, the most serious disease outbreaks in terms of impact on traffic were SARS in 2003 and H1N1 in 2009. Like the COVID-19 pandemic, these infectious respiratory diseases spread via respiratory droplets and close contact (Noh et al., 2020) and even airborne transmission via aerosols (Leung and Sun, 2020). With the characteristics of large volume transport capacity and enclosed spaces, traditional transport vehicles (including bus, metro, rail, ship and aircraft) provide key conditions for person-to-person virus transmission (Hasselwander et al., 2021). Besides, the more enclosed travel space during taxi trip also contributes to the spread of infectious disease between driver and passenger. Zhu et al. (2012) applied a CFD-based numerical model to numerically assess the risk of airborne transmission of various infectious diseases, which proved that the insufficient ventilation and overcrowded conditions in public transportation microenvironments. Ground transportation networks as well as air travel play a crucial role in the dissemination of seasonal and pandemic influenza viruses (Cai et al., 2020). In addition, Lee et al. (2021) investigated the early intervention strategies based on the non-pharmaceutical public health measures of isolation and commuting restrictions, which found that the incidence rates reduced by 14–26% within the Gwacheon under the combined implementation of isolation and commuting restrictions. While social distancing, either through isolation or quarantining is the most effective strategy in controlling such spread, a number of people would have to work and keep mobile for a living. It seems that there’s a trade-off between maintaining the economy and epidemic prevention.

Cycling occurs in open spaces instead of an enclosed environment, which can be an alternative means of mobility because it can be compatible with social distancing. It has only been in recent years that bike sharing programs have experienced extreme growth, like Citi Bike, NYC’s BSS, which officially went into service in May 2013 (Citi Bike, 2020a). This is the first time that this BSS has gone
through such a highly contagious pandemic, namely COVID-19. There is almost no research about the role and performance of bike sharing systems in previous epidemics in the literature. But fortunately, the recent technological advances in internet and communication have made it possible to collect vast amounts of bike sharing usage data with rich spatio-temporal properties, which enables the study of bike sharing travel behavior and mobility patterns under the impact of the COVID-19 pandemic.

2.2. Other disturbances to bike sharing systems

A robust and reliable transport system is critical to social and economic development (Azolin et al., 2020; Tekouabou, 2021). Generally, a transport system like BSS has enough resilience to maintain or quickly recover its functionality after a disruption, but sometimes big changes occur that can even result in destruction of the systems (Teixeira et al., 2020; Fuller et al., 2019). Some relevant studies have explored the impacts of other transportation-related interferences, disruptions, or even destruction on bike sharing systems. Extreme weather is one of the most common conditions that interferes with a BSS, and it has an impact on the overall network in terms of ridership generally. Rainy weather, as well as relative humidity, reduces daily trips for both genders and for all ages (Rabassa et al., 2020; An et al., 2019), while various user communities have different responses when they hear alerts (Rabassa et al., 2020). Li et al. (2018a) explored the relationship between air pollution and bike sharing choice using nested logit and mixed nested logit models, which revealed significant negative impact of air pollution. The effects of local disturbances or special events were found to be non-negligible, which can cause an imbalance of bikes between supply and demand, such as during festivals and parades (Younes et al., 2020). Chatterjee et al. (2013) have found that some life events (outside transport domain) in a number of domains (education, employment, family, residential, health, leisure) are also important for breaking habitual behavior. Fuller et al. (2019) and Saberi et al. (2018) measured the impacts of a public transit strike on bike sharing program use from the aspects of ridership and network, which enhances the understanding of the relationship between bike sharing and public transportation systems. They found that the disruption has a significant influence on the structure, connectivity, and attributes of the bike sharing mobility network, exhibiting a heterogeneous distribution over space of the observed changes. The addition of a new transport facility, like a metro line or metro system (Gu et al., 2019; Sun et al., 2020), also has an impact on the existing bike sharing program, whether they inter-enhance or inter-replace each other. Given the differences of gender, age, and trip purpose in travel mode choice, it’s worth noting that there are different sensitivities of the above attributes on the bike sharing systems change. Overall, the variations of ridership, network structure, and user communities of bike sharing systems are the emphasis of this study.

3. Case study region and data acquisition

3.1. Study site

NYC is selected as the study area. NYC is the most populated city in both NY State and the US; the city contains five boroughs (see Fig. 1). It houses 8.51 million people with a huge daily travel demand (NYCdata, 2018). With more than 150,000 active annual members, Citi Bike, NYC’s BSS, is the largest bike sharing system in operation in the US and provides efficient service for travelers (Citi
Bike, 2020b). Currently, it has approximately 14,500 bicycles allocated at 1027 stations concentrated in Manhattan, Brooklyn, Queens, and Bronx (Citi Bike, 2020a).

3.2. Data description

The BSS dataset used in this study includes over 28 million bike-sharing trip records between January 01, 2019 and 06/30/2020, which were downloaded from Citi Bike’s official website (Citi Bike, 2020c). It covers a six month period of the COVID-19 pandemic beginning in 2020 and the previous year. Each record in the dataset consists of trip duration, start time and stop time, and includes geolocated start station and end station, user type, birth year and gender. A sample of the BSS dataset is shown in Table 1. As suggested by Ji et al. (2020) and Du et al. (2019), outlier trips with inconsistent travel durations (<1 min or >6 h) were removed from the assessment.

4. COVID-19 pandemic in NYC

COVID-19 is a global pandemic caused by Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) (Shechter et al., 2020). On January 22, 2020, COVID-19 unfortunately struck the US and the first case was reported. Shortly after, a total of 14 cases of COVID-19 appeared in six US states; most of them were from travelers who were either arriving from abroad or had close contact with people having confirmed infections (CDC, 2020). However, the majority of the subsequent cases were attributed to community-based spread, because from the infected people had no recent travel or links to known confirmed cases (The New York Times, 2020). The World Health Organization (WHO) officially declared the COVID-19 pandemic on March 11, 2020 (Stat News, 2020). Displayed in Fig. 2 is the timeline of major events in the development of the COVID-19 pandemic.

During the ongoing COVID-19 pandemic in the US, many states experienced a significant increase in the number of cases and deaths, including New York State. Particularly, NYC is a global epicenter of the COVID-19 pandemic. Looking back on the development of the disease in NYC, the first case of COVID-19 was confirmed on March 2 and a range of public health responses was triggered in March. For example, the NY governor declared a state of emergency on March 12, and by March 20, he officially put “NY on PAUSE.” A stay-at-home order went into effect at 20:00 on that day. Also, other relevant policies such as lockdown measures, social distancing measures and online working measures were enacted throughout NYC. In other words, NYC conducted a month-long blitz of intense response to the COVID-19 pandemic in March.

When NYC became a region with limitations restricting people’s movements, the effects of these executive orders were significant and strong enough to potentially change people’s travel choices and travel patterns. As a popular travel mode that is closely linked with a citizen’s daily life, how might bike sharing usage changes during the pandemic? Specifically, what happens to the intensity and regularity of bike sharing usage at a spatial-temporal level? Does the outbreak of the COVID-19 pandemic have an effect on the bike sharing demand networks? Are there nuances of bike sharing demand that exist substantially across demographic groups and user types in the context of the COVID-19 pandemic? To seek answers for these questions, this study focuses on the performance of the bike sharing system of NYC over long periods of time, while attempting to explore the impacts of the COVID-19 pandemic on people’s attitudes about this disease and subsequent changes in travel behavior.

5. Analysis of bike sharing patterns during the COVID-19 pandemic

This section first outlines the bike sharing usage variation over time at a spatial-temporal level. Subsequently, it presents a supplementary analysis of the impact of the COVID-19 pandemic on the bike sharing mobility patterns from the perspective of complex network. Finally, a multivariate investigation of user and trip characteristics on the bike sharing system is conducted from a microscopic perspective.

5.1. Spatial-temporal patterns of bike sharing trips

5.1.1. Temporal patterns

Visualization is a powerful technique to capture characteristics of various things intuitively (Huang and Sun, 2019; Li et al., 2018). This section explores bike sharing usage regularity across different spatial and temporal scales. Fig. 3 displays the temporal distribution

Table 1

| Trip duration (s) | Start time | Stop time | Start station id | End station id | User type | Birth year | Gender |
|-------------------|------------|-----------|------------------|----------------|-----------|------------|--------|
| 534               | 2020/4/1 00:00:15 | 2020/4/1 00:09:10 | 3656         | 545         | Subscriber | 1990 | 2 |
| 529               | 2020/4/1 00:02:29 | 2020/4/1 00:11:18 | 3163         | 3301         | Subscriber | 1974 | 1 |
| 1488              | 2020/4/1 00:02:56 | 2020/4/1 00:27:44 | 3164         | 3605         | Subscriber | 1982 | 1 |
| 341               | 2020/4/1 00:03:25 | 2020/4/1 00:09:06 | 3827         | 3869         | Subscriber | 1996 | 1 |
| 2206              | 2020/4/1 00:05:35 | 2020/4/1 00:42:22 | 3890         | 3058         | Customer   | 1977 | 1 |
| 534               | 2020/4/1 00:05:50 | 2020/4/1 00:21:12 | 3697         | 3360         | Subscriber | 1986 | 2 |

aGender = 1 if person is female; = 2 if person is male.
of daily bike sharing ridership from the beginning of 2019 through June 2020. Intuitively, the figure shows that bike sharing demand fluctuated slightly without much change or volatility, before the outbreak began to take a grip on the US. This steady-state of bike sharing demand continued up to the beginning of the outbreak in NYC (around early March), indicating that people in NYC were initially on the alert without changing their travel plans because their local health situation was positive, even if many cases of COVID-19 were reported in the rest of the country. When the first local case was confirmed in NYC and a series of strategies of containment for the pandemic were conducted, bike sharing system in whole March witnessed a sharp fall in usage and reached its 18-month lowest point at the end of March. In April, bike sharing ridership starts to bounce back after people become comfortable with lockdowns, quarantines and isolations, but not by much. One of the major reasons for this might be that people who have stayed at home for a long time need to find new mental and material stimulation by going outside home to meet themselves. Another reason could be that the number of new daily cases and deaths of COVID-19 has begun to fall. NYC seems to have been able to effectively control the spread since May (see Fig. 2B), thanks to a series of serious containment measures. However, disease control still remains a tough challenge outside NYC. Accordingly, it’s noted that there is dramatic resurgence of bike sharing usage, which begins in May. The recovered bike sharing system performance has basically been restored, and the bike sharing demand is consistent with the same period last year. Although high infection rates have prompted policymakers to introduce drastic measures limiting people in everyday life and also in traveling, cycling allows people to plan their trips and ensure their own safety while obeying the rules. Several recent studies have been conducted on how bike sharing users reacted during the different phased of the Coronavirus spread (Song et al.,
Based on the research experience of the temporal division, the outbreak timeline in this study can be divided into four periods with consideration of the long-term change tendency of bike sharing usage and epidemic: vigilant period (January & February), pandemic strike period (March), adjustment period (April) and recovery period (May & June), which depicts the general characteristics of each period. Accordingly, the following analysis is conducted based on this division approach.

A closer examination of the time-series hourly bike sharing ridership more clearly reveals the individual features in various periods and impact of the COVID-19 pandemic on people’s travel habits and bike sharing usage regularity, as shown in Fig. 4a. Overall, there are obviously two ridership peaks of the day, which occur around 9:00 and around 18:00. Intuitively, when the pandemic strike begins in the US, a clear decrease in the number of bike sharing trips compared with last year is observed, whether during morning peak or evening peak. However, it’s worth noticing that bike sharing demand has a much greater reduction during morning peak than during evening peak, such that the passenger flow morning peak almost tends to disappear by the time the adjustment period begins. After that, bike sharing ridership begins to rebound quickly with the increased frequency of travel activities. However, the performance of the bike sharing system during morning peak has not yet regained its pre-recession peak due to the effect of the COVID-19 pandemic on people’s travel behavior. There was a significant decline in commuter usage, partly because both employers and employees may have adapted to the flexible working arrangements in terms of the place of work, time of work and continuity of work, since the

Fig. 3. Time series of daily number of bike sharing trips (blue line) and its 7-day average value (red line).

Fig. 4. (a) Temporal variability of number of bike sharing trips during the four periods; (b, c, d, e) Temporal variability comparisons of the boarding ridership and alighting ridership counts.
implementation of work from home during the pandemic (Fatmi et al., 2021). More bike sharing trips for non-commuting purposes (e.g. leisure, sport, entertainment) are generated during the afternoon, which suggests that more concentrated bike sharing usage has already become a new travel pattern in the face of an outbreak.

On the other hand, Fig. 4b–e shows the differences of bike sharing demand between the origin side and destination side within four divided periods; the two cases (boarding ridership is greater or less than alighting ridership) are colored blue and red. Color differences are reasonable because there is a time delay involved in the process of using bike sharing. Although the overall trend of bike sharing ridership both on the origin side and destination side are similar at each stage, the delays start to get longer after the outbreak began to take a grip on NYC. This finding is consistent with previous study which found that the COVID-19 pandemic encourages people to travel less, but with longer trips when they do travel (Hu et al., 2021; Li et al., 2020).

5.1.2. Spatial patterns

This section further analyzes the dynamics of spatial patterns across different time periods on both the origin side and destination side. Spatial distribution of bike sharing usage is visualized first based on the ZIP Code Tabulation Area (ZCTA), where the color of the ZCTA represents the percentile location of the bike sharing usage per unit area within it among whole ZCTAs (see Fig. 5). Measured by bike sharing trip counts, almost all of ZCTAs experience few overall changes over different periods, while the ZCTAs within parks show obvious changes. Specifically, the bike sharing trips generated in these ZCTAs where the parks (e.g. Central Park, Cadman Plaza Park, and Fort Greene Park) are located have increased by about 200% over the outbreak. Significantly, 21 bike sharing stations along the streets nearest the Central Park saw an 237.6% increase in usage during the pandemic strike period, despite the average ridership decreases by 12.8% in other stations within 300m (excluding the 21 stations). The significantly increased counts of bike sharing trips in the above areas most likely resulted from the suggestion (which government agencies encouraged) that exercising during the COVID-19 period helps for boosting immunity.

Considering the third dimension of space, the temporal bike sharing usage regularity pattern may vary across different geographic regions and stations. Fig. 6 maps the change ranges of bike sharing demand during various stages relative to last year’s performance at station level. The station level analysis can capture the dynamics of the whole network mobility distribution under the influence of the pandemic. As shown, the outbreak of the COVID-19 pandemic in the US results in an across-the-board drop in bike sharing ridership, even before the outbreak had begun to take a grip on NYC. When the first case of COVID-19 was reported in early March, bike sharing ridership dropped more significantly in lower Manhattan than other regions since the region is mainly surrounded by workplaces. People started to work from home rather than in the office. The regional differences in bike sharing usage become apparent during the adjustment period that results in high spatial heterogeneity, and a closer look of the figure reveals that the overall demand level is not changing a lot within upper Manhattan. This bike sharing usage pattern also reflects travel purposes related to entertaining or exercising. Most interestingly, a large intra-study-area variation is seen in bike sharing demand with both increasing and decreasing trends. Specifically, a decrease in bike sharing usage is mostly seen in lower Manhattan, whereas densification and high-usage are seen at the edge of Citibike’s coverage zone. The outbreak of COVID-19 in NYC increased the total number of bike sharing trips by around 200% at the edge of the operating area, which results in an active and massive expansion of service coverage and station network near the marginal areas.

Fig. 5. Spatial distribution of total bike sharing trips counts (a) at the origin side and (b) at the destination side.
5.2. Complex network analysis: concept and results

5.2.1. Statistical properties of bike sharing demand networks

This section details a comparative quantitative analysis of the influences of the COVID-19 pandemic on the bike sharing mobility patterns using a complex network approach. Urban transportation is regarded as a complex densely connected network of individuals’ activity spaces, where the individual components are represented by the nodes and the interconnections are the links. From a network perspective, each bike sharing station can be viewed as a node, then the start station node $i$ and end station node $j$ are connected by links with non-negative weights $w_{ij}$ if one or more bike sharing trips are generated between them. The total number of nodes and links in the network are denoted as $N$ and $L$ respectively.

Specifically, the node degree $k$ in a complex network is the number of links connected to a station, which can be calculated as:

$$k_i = \sum_j a_{ij}$$  \hspace{1cm} (1)

where $a_{ij}$ represents the elements in the adjacency matrix. The average node degree in the network is denoted as $\langle k \rangle$.

The node flux $F$ is defined as the total number of trips starting or ending at a station. Generally, this indicator is used to measure the attractiveness of a bike sharing station and its interaction strength in connection to other stations in the network. This $F$ statistic is given by Eq.(2):

$$F_i = \sum_j w_{ij}$$  \hspace{1cm} (2)

where $w_{ij}$ is the weight or the number of trips between each pair of station. Similarly, $\langle F \rangle$ is defined as mean node flux.

The clustering coefficient $c$ is a measure of the degree to which the stations in the network tend to cluster together, representing a more rigorous interaction with one another compared to the other stations outside of the cluster, defined as follows:

$$c_i = \frac{\text{number of trips of neighbors of station } i \text{ that are connected}}{\text{number of trips of station } i}$$  \hspace{1cm} (3)
Meanwhile, the extent to which nodes in the network are clustered from a global perspective is represented by $C$, namely the network clustering coefficient. It’s noted that $C$ is estimated as a ratio of the number of triangles to the number of connected triples of stations, formulated as:

$$C = \frac{\text{number of triangles}}{\text{number of connected triples}} \times 3$$

(4)

Here, one analyzes the resulting connected network of bike sharing trips from consecutive months, before and during the strike of the COVID-19 pandemic. A range of common travel demand network statistical characteristics during various periods is summarized in Table 2. Except for the recovery period, the resulting connected network of bike sharing trips during the COVID-19 pandemic has the same nodes $N$ as last year while its number of links $L$ is less than half of last year’s number. The bike sharing system is almost back to normal since the recovery period and even exceeds it. This is mainly due to the expansion program of the bike sharing network during the outbreak. Similarly, this yields a lower connectivity of the bike sharing mobility network before the recovery period with $L/N = 220.946$ and $\delta = 0.502$ (vigilant period), $L/N = 207.043$ and $\delta = 0.466$ (pandemic strike period), $L/N = 176.407$ and $\delta = 0.398$ (adjustment period), compared to before the outbreak with $L/N = 376.133$ and $\delta = 0.917$ where $\delta$ and $L/N$ representing network connectivity. Specifically, it’s worth noting that the total number of riders per day during the outbreak (40,604, 35,045, and 23,071) is obviously less than that in normal time (57,660), suggesting that people may make fewer trips than usual if they aren’t necessary. However, there has been a remarkable increase in bike sharing usage near some essential places, such as supermarkets, parks and hospitals, with volumes increasing around 200%. For example, considering a catchment area of 200 m from the hospital or supermarket, the bike sharing stations near the major related places have indeed increased its ridership than previously, up 186.1 percent (vigilant period), 165.0 percent (pandemic strike period), and 177.2 percent (adjustment period) in average respectively. It means that bike sharing is more likely to be used for some inevitable travels during the outbreak, reducing people’s destination heterogeneity. The connectivity of the bike sharing trip network during the recovery period remains roughly the same as under normal conditions.

The average node degree in the complex network of bike sharing trips in 2019 is $< k >= 386.916$, which is nearly two times greater than the average node degree before the bike sharing system started to recover, with $< k >= 217.749$ (vigilant period), 208.036 (pandemic strike period), and 177.407 (adjustment period). This exhibits a weaker interaction between bike sharing stations across the network caused by the COVID-19 pandemic in the early stage of the outbreak. For the same reason, the coefficient of variation of node degree of $CV(k)$ is greater in the early stage of the outbreak by one time compared to last year. The bike sharing networks with lower $< k >$ and higher $CV(k)$ during the vigilant period, pandemic strike period, and adjustment period, seem to confirm that a larger heterogeneity in connectivity existed between bike sharing stations; however, ridership imploded at some stations in the early stage of the COVID-19 outbreak. Later, the whole bike sharing system is bouncing back as social life activities begin to resume.

The results of node flux $F$ are slightly different than node degree $k$. While the outbreak of the COVID-19 pandemic wipes out nearly half of average node flux $< F >$ during the vigilant period and the pandemic strike period, the variability of $< F >$ measured by the coefficient of variation $CV(F)$ increases slightly. Taking the lower average node degree $< k >$ into consideration during the two periods, it could also suggest that there was a greater heterogeneity distribution of interaction strengths and connectivity between bike sharing stations before the NY governor took political decisions, revealing a highly homogenized behavior due to the disruption in the system. Surprisingly, although the average node flux in the initial implementation of a series of executive orders is 769.74 (which is less than a third of the value from last year $< F > 2364.03$), there is only a slight reduction in the node flux variability $CV(F)$ (from 0.925 to 0.863). The inconsistent change of the two indicators shows that health measures have a negative effect on the attractiveness of some bike sharing stations and the interaction strength in connection to other stations, while having hardly any effect on the distribution of interaction strengths across the network. Similarly, the bike sharing system vitality has started to restore as people in NYC have adapted to the new travel patterns during the COVID-19 pandemic.

Table 2
Explanation of statistical properties of bike sharing mobility network and corresponding measurement results during the four periods.

| Level          | Statistical property | Description                      | Vigilant period | Pandemic strike period | Adjustment period | Recovery period |
|----------------|----------------------|----------------------------------|-----------------|------------------------|-------------------|-----------------|
| Basic features | $N$                  | Number of nodes                  | 881             | 889                    | 887               | 958             |
|                | $L$                  | Number of edges                  | 194,653         | 184,061                | 156,473           | 333,338         |
|                | $L/N$                | Network connectivity             | 220.946         | 207.043                | 176.407           | 347.952         |
|                | $\delta$             | Network connectivity             | 0.502           | 0.466                  | 0.398             | 0.726           |
|                | $T$                  | Total number of trips per day    | 40,604          | 35,045                 | 23,071            | 56,258          |
| Global features| $< k <$              | Mean node degree                 | 217.749         | 208.036                | 177.407           | 348.952         |
|                | $< F >$              | Mean node flux                   | 1329.3          | 1201.86                | 769.74            | 1758.96         |
|                | $< w >$              | Mean edge weight                 | 6.105           | 5.777                  | 4.339             | 5.041           |
|                | $CV(k)$              | Coefficient of variation of node degree | 0.493         | 0.506                  | 0.502             | 0.404           |
|                | $CV(F)$              | Coefficient of variation of node flux | 1.048         | 0.931                  | 0.863             | 0.905           |
|                | $CV(w)$              | Coefficient of variation of edge weight | 0.677         | 0.524                  | 0.416             | 0.614           |
|                | $< c >$              | Mean clustering coefficient      | 0.32            | 0.35                   | 0.41              | 0.29            |
|                | $< wc >$             | Mean weighted clustering coefficient | 0.43          | 0.46                   | 0.49              | 0.39            |
|                | $C$                  | Network clustering coefficient   | 0.27            | 0.31                   | 0.26              | 0.21            |
The values of average edge weight $<w>$ and edge weight variability $CV(w)$ reveal a general trend of rising after falling. Different from average node degree and average node flux, the average edge weight is a lagging indicator. Specifically, the average edge weight during all four periods are 6.105, 5.777, 4.339 and 5.041, respectively. It’s found that the extent of decrease and increase in these early days of the outbreak and in the recovery period of bike sharing system respectively is very little. Given that the average node flux fluctuates acutely, the observed pattern in average edge suggests that many trips generated between the specific bike sharing stations may not decline (or grow) nearly so fast with decrease (or increase) of ridership at the stations involved. In addition, the edge weight variability which is reflected in $CV(w)$ has a lower value during the COVID-19 pandemic, showing a more homogeneous distribution of trip counts between stations while nodes can be less homogeneously connected.

As to the spatial pattern of agglomeration, both the average clustering coefficient $<c>$ and average weighted clustering coefficient $<wc>$ increase before the recovery period. The growth is indicative of a more locally connected bike sharing trip network. Meanwhile, the cluster coefficient can be used to measure the formation of groups or communities in networks. From a global perspective, the network clustering coefficient $C$ is a global measure of the extent to which nodes in a network are clustered. $C$ during the COVID-19 pandemic is larger than last year, revealing a lower connectivity between the bike sharing stations and larger spatial distribution of stations.

These measures provide a basic quantitative picture of the complex network of bike sharing trips over time. However, partial observed differences might be related to the difference in the number of bike sharing stations. Furthermore, this study normalizes each measure by the mean value of the same measure during each period and then plots the normalized cumulative distribution functions respectively. The complementary cumulative distribution function (CCDF) is defined as $P(X \geq x) = 1 − F(x)$ where $F(x)$ is the cumulative distribution function. Fig. 7 compares the CCDF of node degree $k$, node flux $F$, and edge weight $w$. The results show that the node fluxes throughout the time following an almost identical distribution, while the distribution of node fluxes during the pandemic strike period and adjustment period is slightly shifted to the right, indicating that the probability of observing a node with a given flux $F$ is higher during the above two periods compared to the other periods. Although the underlying dynamics of these networks don’t follow a similar fundamental process, the curves for the pandemic strike and adjustment periods are higher than the others for $k$ and $w$. The findings also demonstrate that the bike sharing mobility networks have undergone great changes in these early days of the outbreak (i.e. March and April).

### 5.2.2. Network dissimilarity: Kullback-Leibler divergence (KL-divergence)

The Kullback-Leibler divergence similarity estimation (KLSE) method is a widely used information theoretic measure of the divergence between two probability distributions, which has been successfully implemented for pattern recognition and statistic application (Ponti et al., 2017). Meanwhile, KLSE has emerged as a powerful technique to measure the difference between two probability distributions, which has been successfully implemented for pattern recognition and statistic application. From a global perspective, the network clustering coefficient $C$ is a global measure of the extent to which nodes in a network are clustered. $C$ during the COVID-19 pandemic is larger than last year, revealing a lower connectivity between the bike sharing stations and larger spatial distribution of stations.

Information theory is based on probability theory and statistics (Wong and Farooq, 2020; Wang et al., 2019), and entropy is the most critical quantity of information. Specifically, information entropy can be represented as follows:\n
$$H(X) = − \sum_i p(x_i) \log p(x_i)$$  \hspace{1cm} (5)\n
where $p(x_i)$ is the probability of event $x_i$ occurrence. Based on the information entropy, the KL-divergence can be calculated as follows:

$$D_{KL}(P||Q) = \sum_i p(x_i) \cdot (\log p(x_i) − \log q(x_i))$$

$$D_{KL}(P||Q) = \int p(x_i) \cdot (\log p(x_i) − \log q(x_i)) dx_i$$  \hspace{1cm} (6)\n
(6) where $D_{KL}(P||Q)$ is the difference between probability distributions of P and Q. It’s noted that the calculation of $D_{KL}(P||Q)$ is classified as either discrete or continuous. Obviously, the probability distributions of the selected variables are discrete, hence,

Fig. 7. Statistical properties of the bike sharing mobility network. CCDF of (a) node degree $k$, (b) node flux $F$, and (c) edge weight $w$ during the four periods.
multi-modal connectivity. Interestingly, the percentage of round trips in all the bike sharing trips has increased by nearly four times.

Outbreak began to take a grip on the US, the customer share halved from 15.5% to 7.8%. Subsequently, the share of customers has predominantly used by males (about two-thirds of male users), suggesting gender differences are particularly striking in bike sharing. Females involved both improvements in the urban infrastructure and educational campaigns for cyclists should be implemented to ensure gender equality in bike sharing participation and use. Numerous scholars have critically analyzed the gender gap in bicycling choice and found that females predominantly used by males (about two-thirds of male users), suggesting gender differences are particularly striking in bike sharing. Therefore, the positive changes of female users in bike sharing, to some extent, reflect the greater emphasis placed on their own health.

It is clearly that bike sharing can be compatible with social distancing, either for daily activities or exercise. To examine whether and how bike sharing user communities differ with regard to the development of the COVID-19, Table 7 presents the personal and trip characteristics periods. Generally, the number of female bike sharing cyclists increased after a small decrease during the vigilant period. Females are more likely than males to have flexible jobs (Cook and Grimshaw, 2021; Parlak et al., 2021). They might commute to balance work and family and to catch up on work, if there is a potential infection risk. This could be the reason why the proportion of female users has reduced during the vigilant period. Then, the proportion of female users continued to increase from 23.6% to 36.0% since the outbreak of COVID-19, partly out of concern for their own health (Amendola et al., 2021; Colley et al., 2020). It is clearly that bike sharing can be compatible with social distancing, either for daily activities or exercise. Therefore, the positive changes of female users in bike sharing, to some extent, reflect the greater emphasis placed on their own health.

Meanwhile, despite incremental increases in use amongst females during the outbreak, the current bike sharing system is still predominantly used by males (about two-thirds of male users), suggesting gender differences are particularly striking in bike sharing use. Numerous scholars have critically analyzed the gender gap in bicycling choice and found that females’ concerns for safety (Wang and Akar, 2019a), their different bike sharing needs (Beecham and Wood, 2014) and reliance on bike-friendly infrastructures (Böcker and Anderson, 2020) can explain why, in most cities, fewer females participate in bike sharing. Yet it is worth noting that the superiority of bike sharing shown during the COVID-19 has to some extent attracted more females to access to cycling, but it’s not enough. Given that a sustainable transport system requires providing equitable mobility across the gender line, more policies targeting females involved both improvements in the urban infrastructure and educational campaigns for cyclists should be implemented to ensure gender equality in bike sharing participation and use.

Bike sharing usage increased significantly among young and middle-aged people under the age of 35, but declined significantly among the group aged 35 and over, especially middle-aged and older people. Of the bike sharing users, most are subscribers. When the outbreak began to take a grip on the US, the customer share halved from 15.5% to 7.8%. Subsequently, the share of customers has surged to 31.2%. One of the major reasons for this change might be that more and more people are now willing to experiment with a bike sharing program. Bike sharing trips can be single or round trip, allowing the bicycles to be used for one-way transport and for multi-modal connectivity. Interestingly, the percentage of round trips in all the bike sharing trips has increased by nearly four times.
since the bike sharing system usage intensity restored to pre-pandemic conditions. This result is consistent with the findings from previous studies that people are more likely to use a shared bike to take a longer round-trip ride for exercise.

During the outbreak response, frequent outdoor activities may increase vulnerability to infection of the novel coronavirus. Accordingly, it’s necessary to develop efficient measures for the outdoor time control and even outdoor activities prohibition. Specific

### Table 4
KL-divergence of node flux $F$.

|                      | Vigilant period | Pandemic strike period | Adjustment period | Recovery period |
|----------------------|-----------------|------------------------|------------------|-----------------|
| Vigilant period      | 0               | 0.49                   | –                | –               |
| Pandemic strike period| –               | 0                      | 0.41             | –               |
| Adjustment period    | –               | –                      | 0                | 0.38            |
| Recovery period      | –               | –                      | –                | 0               |

### Table 5
KL-divergence of edge weight $w$.

|                      | Vigilant period | Pandemic strike period | Adjustment period | Recovery period |
|----------------------|-----------------|------------------------|------------------|-----------------|
| Vigilant period      | 0               | 0.17                   | –                | –               |
| Pandemic strike period| –               | 0                      | 0.15             | –               |
| Adjustment period    | –               | –                      | 0                | 0.09            |
| Recovery period      | –               | –                      | –                | 0               |

### Table 6
KL-divergence of clustering coefficient $c$.

|                      | Vigilant period | Pandemic strike period | Adjustment period | Recovery period |
|----------------------|-----------------|------------------------|------------------|-----------------|
| Vigilant period      | 0               | 0.92                   | –                | –               |
| Pandemic strike period| –               | 0                      | 1.22             | –               |
| Adjustment period    | –               | –                      | 0                | 1.08            |
| Recovery period      | –               | –                      | –                | 0               |

### Table 7
Personal and trip characteristics by periods.

|                          | Vigilant period | Pandemic strike period | Adjustment period | Recovery period |
|--------------------------|-----------------|------------------------|------------------|-----------------|
| Personal characteristics  | $N$ %           | $N$ %                  | $N$ %            | $N$ %           |
| Sex                      |                 |                        |                  |                 |
| Men                      | 868799 76.4     | 722979 73.3            | 412624 68.3      | 930857 64.0     |
| Women                    | 268092 23.6     | 263862 26.7            | 191812 31.7      | 523471 36.0     |
| Age group                |                 |                        |                  |                 |
| < 18                     | 1107 0.1        | 1116 0.1               | 654 0.1          | 2668 0.2        |
| 18–25                    | 106543 9.4      | 98881 10.0             | 52781 8.7        | 177212 12.2     |
| 26–35                    | 422478 37.1     | 375622 38.1            | 254824 42.1      | 662100 45.4     |
| 36–45                    | 267627 23.5     | 225006 22.8            | 135060 22.3      | 297831 20.4     |
| 46–59                    | 260208 22.9     | 218599 22.2            | 123942 20.5      | 244507 16.8     |
| ≥ 60                     | 79584 7.0       | 67158 6.8              | 38985 6.3        | 73599 5.0       |
| User type                |                 |                        |                  |                 |
| Customer                 | 93340 7.8       | 154389 14.5            | 166267 24.4      | 525708 31.2     |
| Subscriber               | 1100373 92.2    | 914068 85.5            | 516495 75.6      | 1159374 68.8    |
| Trip type                |                 |                        |                  |                 |
| Round trip               | 18768 1.6       | 38865 3.6              | 55803 8.2        | 119257 7.1      |
| One way                  | 1174946 98.4    | 1029592 96.4           | 626959 91.8      | 1565825 92.9    |

Trip duration, which can be regarded as sojourn time outdoors (sec.)

|                      | Round trip | One way | Round trip | One way | Round trip | One way | Round trip | One way |
|----------------------|------------|---------|------------|---------|------------|---------|------------|---------|
| Trimmed means        | 1061 598   | 1573 778 | 1854 1018  | 1838 1111|
| Median               | 943 552    | 1527 666 | 1772 920   | 1760 1022|
| Std. dev             | 6208 6985  | 14692 13916| 8523 20068| 8261 13572|
| Skew                 | 47 219     | 95 123  | 51 107     | 89 95    |

a Customer = 24-h pass or 3-day pass user.
bSubscriber = Annual member.
cRound trip = Trips starting and ending at the same station.
dOne way = Trips starting and ending at a different station.

since the bike sharing system usage intensity restored to pre-pandemic conditions. This result is consistent with the findings from previous studies that people are more likely to use a shared bike to take a longer round-trip ride for exercise.

During the outbreak response, frequent outdoor activities may increase vulnerability to infection of the novel coronavirus. Accordingly, it’s necessary to develop efficient measures for the outdoor time control and even outdoor activities prohibition. Specific
to bike sharing trips during the pandemic, the trip duration spent on the trip can be regarded as sojourn time outdoors, which deserves
the same consideration. As shown in the bottom half of Table 7, the sojourn time of both round trips and one-way trips practically
doubled. Particularly for bike sharing round trips, the sojourn time rose from 15 min at the start of the COVID-19 pandemic to 30 min
after several months. The smaller standard variance of bike sharing round trips suggests a higher proportion of cyclists with longer trip
duration.

5.3.2. Associations of personal and trip characteristics with sojourn time

This section conducts a further statistical analysis, exploring the relationship between personal, trip characteristics and sojourn
time (see Table 8 below). The results show that female users always tend to ride for longer in different periods, about 1.3 times longer
than male users, perhaps in part because females generally ride at lower speeds than males (Aldred et al., 2015). There is good evidence
that increasing age is associated with the duration of sojourn time. The gap in the age distribution of sojourn time increases slightly
with the development of the COVID-19 pandemic. The significant differences of sojourn time between customers and subscribers are
present during the different periods, surprisingly. Before the outbreak of COVID-19 spreads to NYC and after several weeks of the
pandemic, customers are more likely to take shorter bike sharing trips. However, subscribers, as the annual members, tend to take
advantage of bike sharing service for prolonged riding. Also, it’s found that round trips are more sensitive to the COVID-19 pandemic
than one-way trips, which is consistent with the findings from previous studies that bike sharing usage for physical exercises or
recreation purpose is becoming more and more frequent (Lee et al., 2021; Zheng et al., 2021).

6. Conclusions and recommendations

This retrospective study applied a series of statistical techniques including spatial-temporal approach, complex network-motivated
methodology and cyclist behavior analysis to capture the influence of the COVID-19 pandemic on bike sharing mobility patterns. The
comparative analysis has led to an in-depth understanding of the evolution of a bike sharing system in terms of usage, network
structure, and user community. Again, this study has illustrated the importance of a bike sharing system on people’s daily life during
the outbreak. Using the open data from New York’s Citi Bike system, this study contributes to the existing research efforts on exploring
the role of a bike sharing program in a long-term emergency and the development of special operation measures under the epidemic
environment. Major findings from the exploratory research include:

In macroscopic view, the study found compelling evidence of a significant spatial-temporal difference on bike sharing usage
regularity at different developmental stages of the COVID-19 pandemic. Even though there are wide-ranging changes to bike sharing
ridership, the changing tendency of the temporal distribution of trips is clear. Specifically, there is a large-scale shift in demand related
to previous morning and evening peaks. During the early stages of the pandemic, there was a much greater reduction in demand during
morning peak than during evening peak, such that the passenger flow morning peak almost tended to disappear by the time the
adjustment period began. As to the spatial distribution of bike sharing usage, travel demand drastically decreased across the whole bike
sharing network, even before the novel coronavirus had spread to NYC. However, the observed change in bike trip counts shows
heterogeneity across the network as the outbreak began to take a grip on NYC. Specifically, the bike sharing trips increased slightly in
lower Manhattan, while ridership increased by 200% in other areas, particularly near the parks. The outbreak in bike sharing system
resulted in greater connectivity in the network and an increase in interaction strength between stations, because cycling can serve as an
alternative mode of transport as it can be compatible with social distancing. Although the outbreak did not affect the importance or
centrality of some bike sharing stations, many people may not be making as many unnecessary trips.

Microscopically, results suggest that different user communities react to the outbreak in different ways, thereby affecting bike
sharing usage behaviors. The descriptive statistics show that more than two thirds of the bike sharing trips are made by men generally,
which indicates bike share ridership is strongly skewed by gender. Nonetheless, female bike share riders are more sensitive to the
COVID-19 pandemic and are less likely to make bike share trips when the viruses comes. Meanwhile, the multiple regression analysis
results imply that women may be riding shared bikes for longer time periods than men. The younger bike share riders are, the more
frequently they use the mode of transport for travel. In addition, they have longer sojourn times. More and more new users are trying
the bike sharing system for daily activities or exercise during the COVID-19 pandemic, especially for round trips with longer duration
times.

Currently, it’s too early to discuss all the government measures against the COVID-19 pandemic and how long they will be in place,
let alone to predict the peak of the outbreak or when it will end. There is no doubt that a range of lockdown restrictions to social
activities, communications, and economic activity may lead to a lower income in the long term, affecting both commuting mobility as
well as travel budgets of people for non-commuting trips. More factors will be involved in travel mode choices. Although the COVID-19
impacts and the response of various transport systems are only starting to emerge, bike sharing systems in U.S. cities like NYC have
started to come back because they offer a safe, healthy and cost-effective mode of transport. Certainly, the outbreak (and a range of
public health responses) may have structural, long-lasting influences on travel behaviors and mobility patterns rather than transitory
impacts. More concentrated bike sharing demand during the evening peak, substantial reduction of bike sharing ridership near work-
related places, and the evolution of user communities, are three examples that corroborate how COVID-19 has affected many aspects of
people’s work and life.

Results reveal that a bike sharing system could potentially reduce the load on the urban transport network and improve the
resilience of the transportation systems during the outbreak. Some policy implications and recommendations emerge from the findings
discussed in this study. First and foremost, given that the increased demand for bike sharing systems, it’s necessary to provide a safer
mode of transport with enhanced cleaning protocols, because shared bikes could still be a potential infection source. Second, bike
sharing operators need to prepare contingency plans for the outbreak of a public health event. This may include price and subscription service adjustments, additional dispatching management, and flexible plans for bike docks and stations.

Third, the spatial-temporal patterns of bike sharing usage during the COVID-19 pandemic can offer urban transport management agencies with insights regarding latent demand for shifting a portion of other mode trips to bike sharing, which could help to improve resilience of a bike sharing system in the event of an emergency, such as a strike, parade, extreme weather condition, natural disasters, and facility maintenance. Finally, it is likely that the mode share of bike sharing is not increased in the long run if no policy measures are conducted during the pandemic. Authorities are well-advised to take this opportunity to strengthen cycling (e.g. infrastructure improvement, online cycling classes, and subsidized bike purchase) and to lead to a more reliable, low-cost, flexible, and sustainable urban transport system.

Overall, the focus of the this study has been on examining the influence of the COVID-19 pandemic, which is the first step towards a full understanding of the relationship between the bike sharing systems and the outbreak. Yet, future research could build on this study in several ways. On the one hand, a clearer picture of the role of a bike sharing program in these emergency situations can be refined and confirmed as more relevant studies are conducted in other cities with bike sharing systems. On the other hand, there is a need for longitudinal estimation on bike sharing usage regularity, enabling researchers to explore how the outbreak impacts a bike sharing system over time. Of course, it would probably make more sense to extend the study to a wider population of cyclists involving people who are not bike sharing users if possible.

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Author statement

Hui Bi: Conceptualization, Methodology, Software, Formal analysis, Writing-Original draft preparation.
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