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Spatiotemporal evolving patterns of bike-share mobility networks and their associations with land-use conditions before and after the COVID-19 outbreak

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\textbf{Abstract}
Recent months have seen ever-increasing levels of confirmed COVID-19 cases despite the accelerated adoption of vaccines. In the wake of the pandemic, travel patterns of individuals change as well. Understanding the changes in biking behaviors during evolving COVID-19 situations is a primary goal of this paper. It investigated usage patterns of the bike-share system in Singapore before, during, and after local authorities imposed lockdown measures. It also correlated the centrality attributes of biking mobility networks of different timestamps with land-use conditions. The results show that total ridership surprisingly climbed by 150% during the lockdown, compared with the pre-pandemic level. Biking mobility graphs became more locally clustered and polycentric as the epidemic developed. There existed a positive and sustained spatial autocorrelation between centrality measures and regions with high residential densities or levels of the land-use mixture. This study suggests that bike-share systems may serve as an alternative mode to fulfill mobility needs when public transit services are restricted due to lockdown policies. Shared-micromobility services have the potential to facilitate a disease-resilient transport system as societies may have to coexist with COVID in the future.

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1. Introduction

Severe acute respiratory syndrome coronoavirus-2 (COVID-19) has inflicted enormous life and economic loss in over 200 countries and territories, with a death toll amounting to four million [1]. The viruses spread with an unprecedented rate when authorities fail to close borders, seal off major cities, confine residents at homes, and implement other extreme quarantine measures [2]. These lockdown strategies, along with social distancing, aim at cutting off virus transmission routes, including close person-to-person contact, aerosol, and contaminated surfaces. Reducing or stalling public transport services also helps decrease physical contact during the surges in COVID-19 illnesses. This leads towards a significant decline in ridership and poor performance of urban transportation systems. The disruptions of public transport contribute to higher demands on other modes, such as private driving, walking, and cycling [3]. Among these, cycling is believed to be an appropriate alternative and eases travelers’ fear over contracting the disease as social distance can be ensured. It becomes increasingly low-cost, available, and efficient nowadays because shared bikes are ubiquitous nowadays [4,5].

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Co-existing with COVID-19 appears to be a new norm in many countries. Thus, it is important to understand whether people have shifted mobility preferences under this new norm. These lines of inquiries may help to build a post-COVID transportation system, which have both academic and practical merits. New variants of mobility options have spurred renewed interests among transportation domains. A growing body of publications have reported on the role of bike-share during the closure of mass transit infrastructure [6,7]. As the global health crisis is unprecedented, we have witnessed various impacts upon global economy and transportation systems. Some impacts and underlying mechanism are therefore inadequately addressed. There has been a proliferation of publications regarding bike-sharing and COVID-19, indicating a rise of research probes into these areas. While a number of these studies employed a similar comparative approach to identify spatiotemporal changes during the epidemic evolution, these changes may be insufficiently justified. Some critical questions remain further investigation. For example, if bike-share systems have higher usage rates during the epidemic, what are potential driving forces behind the changes? Our results identified a surprising boom in bike-share ridership, and we demonstrated a transforming spatiotemporal landscape of bike-share usage patterns during various stages of the COVID-19 evolution. The findings of this study aims at strengthening the scientific footings of bikes-share research and providing practical insights into urban and transportation planning that is shifting focuses upon efficiency and resilience. Academically speaking, learning how a bike-share system fulfills the needs of human mobility during a disease outbreak is essential because cities must enter a new norm where the virus may become a part of model society for a while. The coexistence of viruses and human may result in commuting patterns. Working from home becomes a permanent mode in certain sectors where knowledge workers are occupied. Staggering working hours is another option in many workplaces. These indicate a long-term transformation of travel demands which will eventually shape urban transit systems. The academic values of this work lie in investigating how bike-share can play a role during this transforming era. Practically, this work hopes to assist transportation planners and bike-share operators in the aftermath of the epidemic.

Singapore is selected as a case region of this work. Singapore, because of its high population density, is vulnerable to deadly and transmissible respiratory diseases [8]. Singapore reported its first imported COVID-19 case on January 23th, 2020 [9]. Following the first instance, there were sporadic new imported cases. February 4th marked the first community case. Three days later, Singapore’s Ministry of Health declared an orange level of the national Disease Outbreak Response System Condition (DORSCON), meaning that the disease was severe and a community spreading was observed. Around one and half months later, there was a spike in new COVID-19 illnesses and deaths. Hence, on April 7th the government declared that the state entered into circuit breaker, a period when all recreational facilities were closed, people were only permitted to leave their homes to get essential goods, work for an essential service provider, seek medical help, or exercise alone in the proximity of residence. Circuit breaker lasted for nearly two months, before social and economic activities resumed gradually from June 2nd onwards. In summary, the past few months have seen a wave of the tightening and relaxing of control measures.

By taking Singapore as an example, this study investigated how the usage of the bike-share system varied before and during the COVID-19 outbreak, analyzed the variations via bike mobility graphs, and linked the changes in travel patterns with land-use context.

2. Literature review

Droplet, aerosol, and contact are major modes whereby infectious respiratory diseases transmit viruses from one person to another [10–12]. Scientific evidence has also pointed to the possibility of both short-range and longer-range airborne routes of COVID-19, Middle-East Respiratory Syndrome Coronavirus, and other respiratory viruses [13–15]. Unventilated, overcrowded, or poorly ventilated environments further accelerate the airborne transmission of respiratory viruses [16,17].

However, engineering strategies may not function well in public transport vehicles. Public buses, trains, and other mass transit tools have enclosed space and are often overcrowded during rush hours, which exacerbates virus spreads. Coleman et al. [8] collected 89 aerosol samples from the facilities of Singapore’s mass rapid transit (MRT) and reported that about five percent of the samples were positive to various respiratory viruses. Another issue is related to human mobility patterns via public transit and expanded transmission radii. The robust tracking of close contacts has been a critical step towards early precautionary responses to pandemics. Public transport may be a significant factor leading to virus spreads, and the pandemic is a disservice to transit systems as well. Both infectious disease laws and the fear towards the risk of contagion contribute to a plummeting of transit ridership. During severe acute respiratory syndrome (SARS), the public transit ridership in Taiwan plunged substantially, and the restoration took a prolonged period [18]. Accordingly, there is a need of alternative transport modes to satisfy human mobility under such unusual circumstances. Cycling may be such an alternative. There is evidence that the wide popularity of e-scooters in China was partly ascribed to the 2003 SARS outbreak when public transit services were partially closed for a long period [19].

Bike-share has become a recent subject of academic scrutiny. Promoting bike-share, as well as other micro-mobility options such as shared e-scooters and e-bikes, may help lower traffic congestion [20], mitigate gas emissions [21], and in the face of pandemics, enhance the resilience of an urban transportation system [22]. Bike-share is widely deemed as a first- and last-mile connector to other public transport components [23]. More importantly, it also helps to withstand the disruptions in transportation infrastructure and sustain human mobility needs. Saberi et al. [7] found that the amount of
bikesharesystems
bike-share trips nearly doubled after the entire subway system was shutdown in London because of workers' strike. They further discovered that the bike-share network was even more well-connected before the strike. In a similar study, Fuller et al. [6] applied a time-series regression model to investigate the temporal changes of bike-share trips in London before and after the disruption of subway services, and their model also witnessed a phenomenal rise in daily ridership following the disruption. Reilly et al. [24] argued that public transit disruptions have a disproportionate impact upon low-income households, and the supply of available bike-share facilities in these neighborhoods might advance the cost and time efficiency of the entire society. These studies have provided strong evidence for bike-share as an integral part of a urban transportation network and its ability to absorb suddenly spiking travel demand due to public transit disturbance. There are a couple of studies in the literature that aims to unveil the impacts of COVID-19 on bike-share and public transit [22,25]. Their results agreed that both transport modes were interrupted due to the pandemic. However, Teixeira and Lopes [22] demonstrated that bike-share experienced a much less drop in ridership than the subway system in New York and there was evidence of a modal transfer from subway to bike-share.

Understanding spatiotemporal usage patterns is one popular route to investigate bike-share systems that can be treated as traffic flows with both temporal (timestamp) and spatial (latitude and longitude) attributes [26]. Previous research is twofold. The first group of studies has focused on the spatiotemporal perspective, aiming at verifying the correlations between cycling activities and exogenous factors. Spatial and time-series regression models [27], dimension reduction techniques [28], and clustering algorithms [29–31] are primary tools for this line of inquiries. By contrast, the second category of efforts has analyzed bike-share from a different angle, a graph theory perspective [32,33]. Graph theories view cycling flows as edges connecting different nodes, and thus an origin-and-destination map of the flows is essentially a network of nodes and edges. The network topology is an elegant representation of a bike-share system.

Table 1 summarizes recent progress in bike-share studies related to COVID-19, showing that the understanding of COVID-19 impact upon bike-share system is a global interest. First, an overwhelming theme is the understanding of spatiotemporal changing patterns of bike-share usage before and after the public crisis. COVID-19 related lockdown policies have resulted in two major transformations regarding spatiotemporal patterns: origin–destination flow structures and trip purposes [34,35]. COVID-19 related policies have uneven impacts upon the landscape of bike-share usage: areas surrounding public transit nodes such as railway stations witnessed a much higher decrease in bike-share usage than other regions such as parks and residential blocks [36]. Additionally, the number of work related trips declined, while leisure related trips saw a marked rise [37].

Second, all the case studies reviewed showed an apparent reduction of travel demands across different transportation modes including bike-share [38]. However, researchers have demonstrated the possibility of bike-share being the more resilient mode than other counterparts [39].

Third direction of efforts are focused on user behaviors via survey analysis. Bike-share facilities may also transmit viruses as other public means, thus deterring users from using shared bikes frequently [40]. However, survey respondents do view bike-share systems as an alternative during the pandemic [41,42]. Less usage led to a reduction in energy consumption, meaning a benefit to environment [43].

Scientists have also compared travel demands of bike-share trips before and after COVID-19 caused the lockdown of cities and explored underlying factors driving the decrease of travel demands [44,45].

In summary, multi-disciplinary efforts have sought to explore the spreading mechanism of contagious diseases among human communities and the role of public transport in this process. Even through we are aware of the potential impacts of the COVID-19 outbreak upon the urban transportation system in general, and bike-share in particular, we are far from understanding and quantifying such impacts completely as the epidemic is still evolving. Current limited evidence seems to support the claim that COVID-19 is negatively associated with bike-share trip demands, but more case studies are required to justify this claim. Additionally, how land-use context may be spatiotemporally associated with bike-share

| Table 1
| Global studies investigating bike-share usages amid the COVID-19 outbreak. |
| Topics | Highlights | Methods, studies, and regions (selective) |
| Spatiotemporal changing patterns of bike-share systems | Origin–destination flow patterns before and during the pandemic; The impacts of lockdown policies; Changes in trip purposes; | Complex network theories [34] (NA) Survey analysis [35] (AS) Regression [35] (AS) |
| Impacts on other transit modes such as bus and taxi | Overall decreased demand; Bike share seems to be a more resilient option | Regression [38,39] (NA) |
| User behaviors | The mobility of older adults during the pandemic; Less usage due to fear over disease infection; Reduction in energy consumption | Survey analysis [46] (NA) Regression [47] (EU) Complex network theories [43] (AS) |
| Travel demand prediction | Changed trip decisions due to COVID-19; Factors affecting travel demand | Survey analysis [44,45] (EU) Regression [45] (EU) |
| Others | Reviews; | Literature critique [48] (WW) |

Note: AS — Asia; EU — Europe; NA — North America; WW — worldwide.
usage is still inadequately studied. Therefore, this study analyzed how the dockless bike-share system in Singapore responded to COVID-19. It also attempted to reveal the changing mobility patterns of bike-share users before and during the epidemic, taking into account different land use factors.

3. Study area and data

Singapore is a country located in the southeastern Asia and has a total area of 721 km$^2$ and a population of over 500 million, one of the most populous region over the world. As a country advocating public transport, Singapore has one of the most efficient transit system. Its MRT network is consisted of six operational lines with a total length over 203 km. MRT is supported by a dedicated bus route network with over 5000 bus stops covering primary residential, commercial, and employment areas in the state (Fig. 1). The MRT and bus systems contribute to approximate 7.5 million rides per day, over 15 times the daily number of trips made by taxi [49]. The dockless bike-share system in Singapore was launched in early 2017, which is a great addition to the public transport system. There were on average over 10,000 daily rides made by shared bikes after its introduction. The bike-share market has undergone expansion and major transformation. The current fleet size of shared bikes is about 14,000. This number back in 2017 is 5500 [27].

The obtained bike-share data was a collection of temporal logs of every trip from Dec. 1st, 2019, to the end of July, 2020. The logs of a trip were a series of records refreshed every 30 s and contained bike identification number (ID), trip ID, user ID, latitude, longitude, and sequence number. We first extracted the origin and destination information from each trip by only retaining the records with beginning and concluding sequence numbers. Next, we filtered out the trips with origins or destinations that were out of the geographical boundary of Singapore (referred as location error filter). We also discarded those trips with duration less than 1 min (referred as short trip filter). In our dataset, such trips only accounted for less than 1 percent of all samples. Additionally, we deleted the trips with an average speed greater than 35 km/h (referred as speeding trip filer). In Singapore, the speed limit for cycling is 25 km/h, and we believed that those speed records came from logistics trucks that might redistribute bikes among different locations at the time of recording.

Land-use data and the locations of bus stops and bike parking racks were fetched from Data Mall at Land Transport Authority (https://www.mytransport.sg/content/mytransport/home/dataMall.html/). The former was a shapefile containing all the land parcels in Singapore. Each parcel was labeled with one of the 32 land-use categories. Similar land-use classes were grouped into a higher level, which is shown by Table 2. A procedure was developed to generate land-use variables for statistical modeling. First, within each unit of analysis (cells shown in Fig. 1), the area percentage of each class was computed and recorded. Second, the land-use mixture in an unit was represented by the Shannon entropy index, which can be computed by

\[
SE = - \sum_i p_i \log_n p_i
\]

where $p_i$ is the percent of land-use $i$ and $n$ is the number of categories.
Table 2
The reclassification of original land use information.

| New category            | Original land use                                                                                 |
|-------------------------|---------------------------------------------------------------------------------------------------|
| Residential             | Residential, Residential/Institution (e.g., HDB flats, apartments, condos, etc.)                   |
| Commercial and business | Business, Business Park, Commercial/Residential, Commercial, Residential with commercial at 1st storey, Hotel |
| Leisure and recreational| Beach area, Sports/recreation, Park                                                                 |
| Transport               | Road, Port/airport, Light rapid transit, Mass rapid transit, transport facilities                  |
| Other urban             | Educational institution, Place of worship, Utility, Cemetery, Health/Medical care, Civic/Community institution, Agriculture |
| Other land use           | Water bodies, Open space, Reserve site, Special use                                                 |

Table 3
Reproduction of four sub datasets.

| Period          | Start and end dates          |
|-----------------|-----------------------------|
| Pre pandemic    | 12/01/2019 to 01/25/2020     |
| Pre circuit breaker | 02/11/2020 to 04/06/2020    |
| Circuit breaker | 04/07/2020 to 06/01/2020     |
| Post circuit breaker | 06/02/2020 to 07/27/2020    |

Fig. 2. The research framework.

4. Methods

To compare the bike-share activities during different phases of the COVID-19 development, we first divided the original trip data according to four windows that marked milestones of the pandemic evolution in Singapore. Table 3 displays the span of each dataset.

Fig. 2 illustrates the workflow undertaken by this study. First, this study examined the temporal trends of both bike-share ridership and daily confirmed COVID-19 cases, on grounds of the entire dataset. Second, we identified cycling flow clusters during four periods via a community detection algorithm that was realized using each trip and its neighboring flows. The outcomes can delineate human mobility patterns via bike-share before and during the pandemic. Additionally, we built several bike traffic networks on top of the walking areas (WA) of each bus stop to explore the network properties of bike-share usage patterns. Next, the networks were compared by several centrality measures, such as closeness,
betweenness, and PageRank. Finally, the spatial coupling of the centrality measures with different land-use categories were further explored through the methods of statistical correlation and bivariate spatial autocorrelation.

4.1. Flow dynamics analysis

The first question is “how do the intensities and directions of bike flows vary due to the COVID-19 evolution and different times of a day”. Identifying the clusters of similar flows is a key to answer this question. First, a flow is defined as a connection between the origin and destination of a trip record. And similarity is measured by the neighborhood searching algorithm which was developed by Zhu and Guo [50]. Fig. 3 illuminates critical steps from detecting neighboring flows of a trip to building a network based on each pair of neighboring flows. First, a neighborhood of a trip was recognized according to the k-nearest searching criterion. Mathematically, a set of neighboring flows of a trip $i$ can be defined as $NF_i = \{F_j | O_j \in NNO_i \land D_j \in NND_i \}$. A neighboring flow $j$ must satisfy two conditions simultaneously: its origin $O_j$ and destination $D_j$ must be within the k-nearest-neighbor sets of the origin and destination of $i$, respectively.

Based on an appropriate $k$ value, a set consisting of all neighboring flows can be finalized. The distance between each flow pair was calculated as the average of the Euclidean distances of origins and destinations, as illustrated by Distances 1 and 2 in Fig. 3. Hash tables were used to store the distances among flows. The second step was to represent the neighboring flows as a network $G = \{V, E\}$ where $V$ is a set of flows as nodes, and $E$ is a set of edges between neighboring trips. Specifically, the edges in the network are denoted by

$$E = V \times V = \{e_{ij}\}$$

where $e_{ij}$ is the edge between neighboring flows $F_i$ and $F_j$. Each edge is assigned a weight, the inverse distance between the two flows. In other words, a smaller distance denotes a higher weight, indicating the two flows are more similar.

Finally, a community detection algorithm was applied to group similar flows into same clusters. A fast greedy approach, Louvain algorithm, was employed in this study [51]. The algorithm aims at maximizing the modularity of a network, which is a score determining how the community partitioning performs. Modularity quantifies the degree to which a network is divided to smaller communities. The higher modularity, the more dense the nodes within a community have, and the
more sparsely they connect to the nodes outside the community. For our network, modularity can be computed by

\[
MD = \frac{1}{2m} \sum_{ij} \left( d_{ij} - \frac{F_i F_j}{2m} \right) \theta(c_i, c_j)
\]

\[
m = 1/2 \sum_{ij} d_{ij}
\]

where \(d_{ij}\) is the edge weight (inverse average distance) between nodes (nodes) \(i\) and \(j\), \(F_i\) and \(F_j\) are the neighboring flows of \(i\) and \(j\) respectively, and \(\theta(c_i, c_j)\) denoted a community multiplier with \(c_i\) and \(c_j\) being community labels of \(i\) and \(j\), and with a value of 1 if \(c_i = c_j\) or 0 if otherwise.

Louvain algorithm has been applied in both docked and dockless bike-share systems [52,53]. It is an unsupervised process, particularly useful in capturing the community structure of a large-scale network. It runs two phases iteratively. First, it assigns each node in the network as an individual community, and the total number of communities is the that of nodes. Next, it involves the removal of a node \(i\) and the merging of \(i\) into its neighboring node \(j\). After the first phase, the community structure varies and the modularity increases. Particularly, the new community of nodes \(i\) and \(j\) obtains the greatest rise in modularity by merging the node \(i\). Mathematically, such increment in modularity of a community \(C\) by taking up an isolated node \(i\) is computed by

\[
\Delta Q = \left[ \frac{\sum_{ji} + 2K_{i,in}}{2M} - \left( \frac{\sum_{tot} + K_i}{2M} \right)^2 \right] - \left[ \frac{\sum_{ji}}{2M} - \left( \frac{\sum_{tot}}{2M} \right)^2 - \left( \frac{K_i}{2M} \right)^2 \right]
\]

where \(\sum_{ji}\) is the sum of the weights (inverse average distances in the network) of all edges within \(C\), \(\sum_{tot}\) is that of the weights of those edges incident to nodes in \(C\), \(K_i\) denotes the total weights of the edges incident to node \(i\), \(K_{i,in}\) represents the total weights of the edges originating from \(i\) to nodes in \(C\), and \(M\) is the total weights of the network.

The second phase of the algorithm is to create a new network whose nodes are the communities identified in the first phase. A reiteration of the first phase introduces by merging the new communities and calculating modularity gains through Eq. (4). The algorithm stops if either modularity remains realistically consistent, or a peak value of modularity is found. In this work, the outcomes of the algorithm were a number of communities, each of which contained similar bike flows. Because many bike flows were within short distances, the flows in a few communities have largely overlapped origins and destinations. For better illustration, we used a peripheral point of the origins and the centroid of the destinations for all flows in a community to visualize clusters.

4.2. The structures of bike mobility graphs

To answer the second question “how do the characteristics of bike mobility networks evolve before and during the pandemic”, we converted origin–destination (OD) flow data into a graph structure. Such a structure also facilitated the modeling of spatial correlation between network properties and land-use conditions. This structure was different from the one used in the flow dynamics analysis, as this study used the WA of each bus stop to aggregate trip locations and projected each WA as a node in a graph (Fig. 4). Choosing WA as an aggregation criterion depended on two considerations. First, the WA layout allows a heterogeneous representation of the study area where the downtown sees a much higher level of bus stop density than the outskirt. Second, over 97 percent of the trips in this study originated or departed from WA. The radius of WA was set as 400 m. According to Wang et al. [54], 300–1500 m is a reasonable range of WA. Pulugurtha and Agurla [55] further stated that 400 m is the maximum tolerable WA from a bus stop. In our study, there was at least one bike parking rack within a 400-m WA zone for 95 percent of all bus stops. Additionally, it provides a foundation for our following-up study on the relationships between bike-share and transit ridership during COVID-19.

To build a graph structure, we first created WA polygons over all bus stops. QGIS was used to create a Voronoi diagram, and the 400-m buffers of each bus stop were intersected with the Voronoi diagram to obtain the polygons (referred as WA zones hereafter) (Fig. 1). Next, the origin and destination of a bike trip was matched to corresponding WA zones using Python. Thus, an OD matrix was compiled and included the trip amount among different WA zones. The outcome was a network \(G_{WA} = (V, E)\) where \(V\) is a set of nodes (WA zones), and \(E\) is a set of edges, denoted as \(E = V \times V = \{e_{ij}\}\). The weight on an edge \(e_{ij}\) is the total number of trips between nodes \(i\) and \(j\). Fig. 9a exhibits the graph structure of bike mobility before the pandemic.

Centrality indicators provide quantitative assessment on a graph structure and help pinpoint influential nodes. Hence, this study applied closeness, betweenness, and PageRank to measure the centrality of a bike mobility network.

Closeness centrality calculates the degree to which a node is reachable by all other nodes. It is calculated by

\[
C_i = \frac{n - 1}{N - 1} \sum_{j=1; j \ne i}^{N} d(i, j)
\]

where \(n\) is the number of nodes that can reach \(i\), \(N\) the total number nodes, and \(d(i, j)\) is the shortest path distance between \(i\) and \(j\).
Node betweenness quantifies the role of a node as a nexus between other nodes. In transportation studies, it can identify “hubs” in a flow network [56]. It is computed by

$$B_i = \frac{1}{(N-1)(N-2)} \sum_{j=1,m=1;i \neq j \neq m}^{N} \frac{\rho(j, m|i)}{\rho(j, m)}$$

(6)

where $\rho(j, m)$ is the number of shortest paths between nodes $j$ and $m$ weighted by the number of trips on each path, and $\rho(j, m|i)$ is the weighted number of those paths between $j$ and $m$ passing through node $i$.

PageRank generates a ranking of the nodes based on the structure of the incoming links to the nodes. Nodes with very high PageRank values are critical in a flow network because they receive traffic from other nodes with high values, which are crucial subcenters in the structure. PageRank is calculated iteratively. First, all nodes are set with an equal value $PR_i = \frac{1}{N}$. Next within each iteration step, PageRank of a node $i$ is updated by

$$PR_i = (1-d) \frac{W_i}{\sum_{j=1}^{N} W_j} + d \sum_{j \in NE(i)} \frac{PR_j}{L_j}$$

(7)

where $W_i$ is the number of incoming trips to node $i$, $d$ is a damping factor with a default value of 0.85, $NE(i)$ is the set of nodes that link to $i$, and $L_j$ is the sum of trips of out-going links from node $j$. The algorithm iterates until there is a convergence.

**Fig. 4.** An illustration of the generation of walking area zones.
4.3. Spatial coupling of different land-use classes and centrality measures

To answer the third question “are the centrality measures spatially correlated with different land-use categories”, we investigated the statistical and spatial correlations between network centrality and land-use conditions. Spatial correlation describes the geographical interdependence of one or more variables in a study area. It can be global or local. The global test demonstrates whether the spatial patterns are clustered, dispersed, or just a random process, and through the local test, the locations of such patterns may be specified. One common approach is to compute global Moran’s I index. Given a centrality measure (e.g., closeness) and a land-use variable produced via Eq. (1), a bivariate global spatial autocorrelation model was constructed to justify their spatial coupling effect. For instance, the variable \(a\) and \(b\) in the following equation may represent centrality measures and land-use mixture degrees in different WA zones. It is defined as

\[
I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i^a - \bar{x}_a)(x_j^b - \bar{x}_b)}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i^a - \bar{x}_a)^2}
\]

where \(n\) is the number of cells (WA zones), \(w_{ij}\) is 1 if cell \(i\) is adjacent to cell \(j\) and 0 otherwise, \(x_i^a\) and \(x_j^b\) are the values of variables \(a\) and \(b\) in cells \(i\) and \(j\), respectively, and \(\bar{x}_a\) and \(\bar{x}_b\) are the mean value of the two variables, respectively. Global Moran’s I index ranges from \(-1\) to \(1\). A positive value indicates a clustered spatial correlation, whilst a negative I suggests a spatially dispersed association between two variables. If I approaches zero, the spatial distribution is random.

Similarly, local bivariate Moran’s I index can be computed by

\[
I_i = \frac{(n - 1)(x_i^a - \bar{x}_a) \sum_{j=1}^{n} w_{ij}(x_j^b - \bar{x}_b)}{\sum_{j=1}^{n} (x_j^b - \bar{x}_b)^2}
\]

where \(I_i\) is the Moran’s I index of cell \(i\), and the definitions of the other parameters are described in Eq. (8). Local Moran’s I indexes are not bounded, but the interpretation is similar. Two immediate cells with high positive values suggest a high–high clustering relationship.

5. Results

5.1. Bike usage as the COVID 19 evolves

Surprisingly, the number of bike-share trips climbs by two times during the circuit breaker period (Apr. 7 to Jun. 1, 2020), compared with the pre-pandemic level (Dec. 1, 2019 to Jan. 25, 2020). When lockdown measures are partially lifted, total trips are almost fourfold as high in Jul. 2020 as in Dec. 2019. Fig. 5 displays the temporal usage of the bike-share system over the first eight months in 2020. Total rides increase steadily from Dec. to Aug., particularly significant when more outdoor activities are allowed after Jun. Approximately 52% of trips are within the range of 1 to 25 min in duration (Fig. 5b), but on average people spend more minutes on their rides on weekdays than on weekends (Fig. 5d). Cycling trips are within a range of 200 to 2400 m in length (Fig. 5c). Bike usage has two surges a day (around 08:30 am and 07:30 pm), with considerably more trips during the pm peak (Fig. 5e).

We also compared overall trip patterns during the four periods. Cycling behaviors remain largely congruent in terms of duration (25 min on median) and distance (around 2200 m on median) (Fig. 6a and b). Overall, travelers’ temporal patterns are similar across the four windows, with twice usage peaks a day (Fig. 6c and d). The usage spike during morning rush hours is at around 08 or 09 am on weekdays, while the morning peak occurs at 10 or 11 am on weekends.

From the trip descriptions, we may infer that there is an increasing volume of bike-share riders despite the COVID-19 outbreak in Singapore, and lockdown measures have marginal effects on average trip duration, distance, and the time-of-day patterns of the bike-share system.

5.2. The dynamics of bike-share flows

5.2.1. The selection of the k parameter

An appropriate k value must be provided during this step. A large k may result in a trip with too many neighbors and loose spatial granularity, while a small value may lead to a situation where many trips are isolated. Hence, we ran an experiment using the pre-pandemic dataset to plot the distributions of the number of neighbors with a wide range of k values. Fig. 7 indicates that when k equals 215, 95 percent of the trips have at least one neighbor, and over 70 percent of the trips are associated with at least eight neighbors.

5.2.2. Bike flow clusters during four periods

Cycling trip data convey a large quantity of information, but network graphs with overlapped trip routes appear to be extremely cluttered in high-demand regions (for example, Fig. 10), reflecting less informative spatial patterns. Therefore, the flow clustering technique was adopted to remedy such deficiencies of traditional graph-based renderings, and the results exhibit discernible and emerging patterns. We compared cycling flow clusters in the morning and afternoon rush hours on weekdays during different times before and after the COVID-19 spread. Fig. 8 shows the flow patterns on
Fig. 5. Bike usage in Singapore’s bike-share system. (a). The daily ridership from Dec. 2019 to July 2020. (b). Duration (minutes) (+/-SD). (c). Distance (m) (+/-SD). (d). Duration on weekdays and weekends (+/-SD). (e). Bike usage by time of day.
Fig. 6. Bike usage before, during, and after the circuit breaker. (a). Distance (m). (b). Duration (minutes). (c). Time of day (weekdays) (95% CI). (d). Time of day (weekends) (95% CI).

Note: Because of data privacy issues, all trips are normalized to the ratio to the maximum number of trips in each sub figure

Fig. 7. The identification of an appropriate k value. (a). The parameter k and minimal number of neighboring flows. (b). The distribution of the number of neighbors of each trip with a k of 215.
Fig. 8. Flow clusters for (a) morning (6 to 9 am) and (b) afternoon (5 to 8 pm) rush hours on weekdays. Groups 1 to 4 denote the four periods: pre-pandemic, pre-circuit breaker, circuit breaker, and post-circuit breaker.
weekdays within four defined periods (similar phenomena are also observed on weekends). Fig. 8a1 and b1 demonstrate cyclists’ flow clusters during peak hours before there are severe community spreads of the disease. Morning peak hours witness significant inbound trips from peripheral areas to regional centers and the city core (southern coastal areas). In contrast, the cite core becomes a polar with outbound flows during afternoon peaks. An interesting phenomenon is that major inflow regions are immediate to their outflow counterparts, and the majority of flow clusters penetrate within adjacent regions. When the COVID-19 situation continues to evolve in this city state, there exhibit remarkably intensified flow clusters across the island (Fig. 8a2 through a4 and b2 through b4). Flow clusters with more than 1000 trips appear even after public transport resumes normal operations in June, 2020 (Fig. 8b4), indicating that bike-share becomes a more frequently utilized travel mode. Additionally, there are substantially more flow communications between adjacent towns (e.g., Seng kang and Hougang) during circuit breaker than in the pre-pandemic window, particularly during afternoon peak hours (Fig. 8b3 and b1). Several popular cluster destinations during afternoon peaks are noticeable: Marina Bay, Downtown Core, and East Coast park.

The overall landscape of flow clusters across the four periods are similar. Inbound and outbound clusters are geographically heterogeneous during morning and afternoon rush hours. More strikingly, major flow clusters grow as
the COVID-19 situation develops, implying a higher demand for bike-share in both residential towns and the city center. The pre-pandemic results display no flow clusters with more than 1000 trips, but such clusters are ubiquitous (more than 10) after the outburst of the disease. From this we may infer that there may be potential modal transfer to bike-share partly because of the practice of social distancing and reduced public transport services.

5.3. Graph structures of bike mobility

The flow cluster maps present a telling story about the directions and intensities of significant bike traffic, but they are largely descriptive. Graph-based techniques can provide quantitative assessment on the network properties of cycling flows, so that the changes in mobility patterns during the epidemic can be quantified. Figs. 9 and 10 show constructed graphs regarding weekday trips in the “before” and “after” periods. Every node in the graph represents a centroid of the WA zones. Nodes are made comparable according to degree and weighted in-degree to enhance the visualization. Node sizes are proportional to node degrees, the number of a node’s connections. Node degrees are an indication of local connectivity of a graph. Red colors suggest that the nodes have high inbound biking trips, and the edges share the same colors with the nodes to which they are incident. The graphs reflect a multipolar spatial structure: local trips dominate the flow landscape, and there are multiple cores that are anchored around a few high-degree nodes. Such a multi-core layout is distinct from that of bus, train, and other public transit networks where the entire city is well-connected and long-distance flows are common. Additionally, the spatial structure transforms as the COVID-19 situation evolves. Before there is a pandemic, there are two major clusters located in the northern periphery of the city (Fig. 9b). Interestingly, when increasing COVID-19 cases are reported, a surge in bike traffic surfaces in the Downtown Core (Figs. 9a and 10a). There are clearly two types of flow clusters. One cluster is dominated by three red nodes that are closely connected to the others with medium and low weighted in-degrees, a highly hierarchical structure (Fig. 10b). The other is over-represented by one central node that is surrounded by numerous nodes with low degrees (Fig. 10c). The enhanced network visualizations help uncover the patterns of how people move around neighborhoods via the bike-share system before and during the COVID-19 crisis.

Table 4 displays summary statistics of the networks for four studied periods. From the table we can pinpoint several important changes. The number of nodes increases to 3779, up from 3352. The number of edges during the post-circuit breaker period is 45,931, more than double the pre-pandemic level. Similar trends can be seen in mean node degree, suggesting that the average connectivity of the graphs augments. Transitivity is a measurement of the extent to which nodes in a graph become connected and form triangles (local clusters). This indicator rises gradually, meaning that after the implementation of circuit breaker, the bike mobility network is even more locally connected. Regional connectedness appears to be more intense as well, as reflected by the number of weakly connected components. Weakly connected components in a directed network represent the sub-zones where internal nodes are connected to each other and disconnected to external ones. These comparisons reveal critical aspects of the network evolution. The bike-share mobility graph is more local clustered and regionally heterogeneous during and after the city shuts down its non-essential functions and reduces public transport services.

Changes in centrality measures reveal additional phenomenal patterns. In consistent with Table 4, average degree centrality in the fourth window is significantly higher than the pre-pandemic level (Fig. 11a). Closeness centrality assumes important nodes are immediate to other nodes in a graph. Therefore, nodes with large closeness values tend to form local clusters. Fig. 11b indicates that the probability of nodes with high levels of closeness is substantially larger in the post-circuit breaker period than in the previous time windows. This alteration implies that denser local clusters emerge after some of the travel restrictions are lifted. Node betweenness measures critical “bridges” or hubs in a transportation network because the nodes with large values are on the shortest paths of many pairs of nodes. It quantifies the extent to which nodes are well-connected to more distant ones in a network. Fig. 11c shows the estimated probability of betweenness centrality during different windows. Interestingly, the circuit breaker period sees a surge in the proportion of nodes with extremely high levels of connectedness, suggesting the important role of hub nodes when public transport is heavily restricted because of deteriorating COVID-19 situations. Next, we calculated the PageRank for each node, identifying nodes with high levels of inbound flows. In the transportation domain, it is used to demonstrate potential polycentric
transformation. Polycentric transformation often occurs when the number of highly centered (PageRank) nodes declines with an increased share of nodes with medium-to-high PageRank. Fig. 11d shows that nodes with the highest PageRank have the top probability during the circuit breaker period, but the number of nodes with the second-largest PageRank are dominant after the termination of circuit breaker. This change underpins the emergence of sub-centers, which can be corroborated by the birth of additional red nodes highlighted in Figs. 9a and 10a. In conclusion, the bike mobility graphs have undergone major changes in local density and regional heterogeneity as the tightening and loosening of transport restrictions due to the COVID-19 outbreak.

5.4. Bike-share activities and land-use variables

Previous studies have justified the associations between cycling flows with built-environment variables [57,58]. It is also beneficial to verify if such associations are existent or even alter during a severe public crisis such as COVID-19 and how policies may compound such associations. First, Spearman’s correlation was conducted between three centrality measures and different land-use categories. This method was non-parametric and appropriate for data that fail to fit a normal distribution. Fig. 12 suggests three correlation relationships. The residential and land-use mixture factors have a moderately positive correlation (0.3–0.5) with the centrality variables, and it is evident that the correlation is temporally stronger. The leisure/recreational and transportation variables are weakly and positively (0.1–0.2) associated with three centrality measures. Although the commercial/business factor has a negative effect, its value is extremely marginal (0.05–0.1). The other land-use elements seem to be uncorrelated with the three network properties, with a coefficient less than 0.05. A key message is that important nodes are more likely to be overlapped with the areas that have many residential blocks or a high level of land-use mixture, which is consistent with similar research. Furthermore, circuit breaker sees the highest coefficient (0.4) between the residential variable and PageRank. During circuit breaker, nearly all employees must work from home and cannot leave homes for non-essential activities, and thus residential areas become major attractors of biking trips.
Fig. 12. Spearman’s correlation coefficients between centrality indicators (weekdays) and different land-use variables.

Table 5
The global Moran’s I tests between centrality measures (weekdays) and different land use indicators over four periods.

| Land use          | Closeness | Betweenness | Pagerank |
|-------------------|-----------|-------------|----------|
| Commercial/business | ▼         | □           | ▽        |
| Transport         | +         | □           | +        |
| Urban other       | □         | □           | □        |
| Leisure           | □         | □           | □        |
| Residential       | ▲         | □           | △        |
| Land use entropy  | ▲         | △           | △        |

▲ 0.2 ≤ Moran’s I index.
△ 0.1 ≤ Moran’s I index < 0.2.
+ 0 < Moran’s I index < 0.1.
□ −0.1 < Moran’s I index < 0.
▽ −0.2 < Moran’s I index ≤ −0.1.
▼ Moran’s I index ≤ −0.2.

The outcomes of bivariate Global Moran’s I tests further illustrate the relationships between cycling flows and surrounding land-use context over space and time, as shown by Table 5. All the indexes have p-values less than 0.05, indicating there exist significant spatial associations between the network properties and land-use variables. The commercial/business variable has a negative spatial correlation with all the three measures, among which Moran’s I index regarding closeness is less than −0.2. That is, cycling flows and nodes are extremely sparse in the regions with a high concentration of commercial buildings or industrial facilities (such as the western business park and the eastern strip of lands adjacent to Changi Airport). Government services, educational institutes, and other urban areas have negative Moran’s I indexes with the centrality measures, although the values are very small. As reported by previous studies [27], under normal conditions these regions attract or produce cycling trips considerably. However, with the escalated COVID-19 epidemic, cyclists may tend to avoid such crowded places. In line with the correlation analysis, the residential and land-use mixture variables are spatially and positively correlated with closeness, with Moran’s I index greater than 0.2. Such spatial phenomena suggest that a plenty of nodes in a biking mobility network tend to be densely located in the areas with a high proportion of residential units or mixed land uses. This inference is substantiated by the local geographical views displayed in Fig. 10c and b. The former covers the administrative boundary of Punggol, which is a newly developed residential town. The latter is the Downtown Core of Singapore, consisted of hotels, high-rise towers of commercial complexes, culture centers, and many other urban facilities.

In particular, we compared the temporal changes of global Moran’s I indexes between the residential variable and the centrality of biking mobility graphs (Table 6). The clustering patterns between residential areas and cycling activities have been reinforced for the first eight months in 2020, as justified by the Moran’s I index of 0.325 for closeness during the post-circuit breaker period, up from 0.237 (pre-pandemic level). This indicates an expanded volume of local clusters of nodes surrounding many residential buildings. However, Moran’s I index for PageRank dwindles below 0.132, the level...
Table 6
The comparison of bivariate global Moran’s I index between centrality measures (weekdays) and the residential over time.

| Measure   | Period          | Moran’s index | z-score | p-value | Spatial pattern |
|-----------|-----------------|---------------|---------|---------|-----------------|
| Closeness | Pre-pandemic    | 0.237         | 37.377  | <10^{-3} | Clustered       |
|           | Pre-circuit breaker | 0.293       | 44.690  | <10^{-3} | Clustered       |
|           | Circuit breaker  | 0.321         | 49.244  | <10^{-3} | Clustered       |
|           | Post-circuit breaker | 0.325      | 49.314  | <10^{-3} | Clustered       |
| Betweenness | Pre-pandemic    | 0.052         | 8.600   | <10^{-3} | Weakly clustered|
|           | Pre-circuit breaker | 0.059       | 9.874   | <10^{-3} | Weakly clustered|
|           | Circuit breaker  | 0.049         | 7.936   | <10^{-3} | Weakly clustered|
|           | Post-circuit breaker | 0.045      | 7.218   | <10^{-3} | Weakly clustered|
| PageRank  | Pre-pandemic    | 0.132         | 22.397  | <10^{-3} | Clustered       |
|           | Pre-circuit breaker | 0.150       | 25.166  | <10^{-3} | Clustered       |
|           | Circuit breaker  | 0.148         | 24.715  | <10^{-3} | Clustered       |
|           | Post-circuit breaker | 0.127      | 20.727  | <10^{-3} | Clustered       |

before the outbreak. This implies that cycling traffic may direct to other urban areas, when the COVID-19 infections are contained and some of the travel bans are terminated.

Fig. 13 delineates how the percentage of residential lands are locally correlated with closeness centrality of nodes. Primary high–high clusters lie in the southeastern part of this island (Geylang and Bedok), northwestern periphery (Shengkang and Punggol), and northern towns (Woodlands and Yishun). The majority of these clusters grow by assimilating immediate low-high polygons where pre-pandemic closeness centrality is low but they are highly residential, as highlighted by the circle in Fig. 13. This indicates a temporal spillover effect of the residential variable upon the node centrality of biking mobility graphs, under an epidemic situation.

6. Discussions and conclusions

The COVID-19 outbreak led to the loss of one million lives and struck the global economy unprecedentedly, and the epidemic continues to spread worldwide. Many countries have to close borders and lock down cities to stem transmission of the virus. Such policies have detrimental consequences for many sectors, including public transport. Public transport ridership may plummet because of such policies or the fear of spreads of the viruses in overcrowded buses and trains. Whether cycling may be a viable alternative to fulfill people’s essential mobility needs becomes an interesting line of inquiries. Hence, in order to understand human mobility during the pandemic, this study applied graph-based techniques and spatial correlation models into the bike-share system in Singapore. The analyses help strengthen the understanding of changes in usage patterns of the bike-share system and their associations with land-use context as a result of the COVID-19 outburst. Overall, there was an over 150 percent rise in ridership during the circuit breaker period when reduced public transport services were provided, compared to Dec., 2019. The clusters of biking flows with increased intensities and densities were seen in the downtown and waterfront areas. The changes in biking mobility graphs indicated a higher level of local connectivity and the emergence of a multicentric structure after circuit breaker. Additionally, spatial interdependence between the bike graph structures and land-use variables was observed. In particular, the local clustering phenomenon and the polycentric characteristic were spatially correlated with residential areas and the degree of land-use mixture, and the associations strengthened as the COVID-19 situation developed.

The observations in this study demonstrate how bike-share may play a pivotal role in building a resilient urban transportation system. Bike-share has been proved to a good first- and last-mile component in a multimodal transportation system. Furthermore, the boom in ridership during the pandemic indicates that short trips between two MRT stations or several bus stops may be replaced by shared bikes. Hence, bike-share may have the ability to absorb additional travel demands due to reduced capacities of public transit services, while complying with the social distancing requirement.

Another contemplation is how our public transport system should be managed or redesigned in the face of uncertain COVID-19 trends. Under the worst scenario, the outbreak may be long-standing, with multiple surges for another one-to-two years. Authorities may be in the processing of tightening and loosening lockdown measures iteratively, which definitely affects public transport. Increasing the mode share of bike-share to meet the needs of human mobility would be a feasible option. This prompts a cascade of actions that should follow. Transport authorities may grant more quota to deploy additional bikes, and bike-share operators need to rethink the arrangement of shared facilities and implement stricter hygiene protocols to provide virus-free bikes that may be more frequently used. Under an optimistic scenario, the epidemic may terminate several months later as vaccines are available. Planners and policy makers may also use this window to rethink how to transform people’s travel patterns, contributing to a “car-lite” goal. People intend to cycle
when alternative options are limited, but when public transport services are business-as-usual again, it remains unclear if cycling is still widely seen on streets. Building a bike-share friendly environment is a key to sustain casual cyclists’ dependence upon this micromobility mode [59].

Although this study attempted to provide a holistic view, it suffers from a few limitations. First, this study omitted other factors that may affect bike-share ridership, such as weather, users’ attributes, and road facilities. COVID-19 may partly drive the boom in bike-share ridership, while such a linkage was not statistically proved. Second, there are a few assumptions during the pre-processing of datasets. The proposed method to generate walking area zones centered on bus stops does omit around three percent of bike-share trips. This omission may have mild impact upon our case study, because Singapore is populous and well served by a dense bus network. Yet, the generalizability of this method should be discussed on a case-by-case basis. The selection of a speed limit filter to remove abnormal trips largely relies on the cutoff speed. The selected threshold may have contributed to biased filtering of cycling trips. Finally, the modal transfer between bike-share and public transit was not verified because of an absence of public transport data. There are arguments that

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**Fig. 13.** Local spatial autocorrelation clusters of closeness centrality (weekdays) and the residential variable. (a). Pre-pandemic. (b). Post-circuit breaker.
bikeshare may complement or compete with public transport. Similarly, we infer a competing effect arose during the outbreak, which is subject to validation. Our follow-up tasks will focus on these aspects.

CRediT authorship contribution statement

Jie Song: First-round paper revisions, New visualization. Liye Zhang: Literature review, Re-organization of the draft. Zheng Qin: Supervision, Reviewing of the revised draft. Muhamad Azfar Ramli: Paper revisions, Proofreading of the final version.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Zheng Qin reports financial support was provided by National Research Foundation, Singapore.

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