Exploring Spatiotemporal Interaction Patterns of Dockless Shared Bicycle Networks: A Case Study of Shenzhen, China

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Abstract

The explosive development of shared bicycles has changed the way people travel. In parallel with the urbanization process, shared bicycles have emerged as a significant mode of transportation, especially for the first and last mile transit. With the aim of obtaining a comprehensive understanding of the spatiotemporal patterns underlying shared bicycle usage, this study takes Shenzhen, China as a case study. Drawing on the principles and techniques of complex network analysis, the research adopts a spatial grid framework, treating each grid as a node, the flow of shared bicycles as an edge, and the flow frequency as the corresponding weight. Subsequently, the spatiotemporal interaction networks of different periods of working days and weekends are constructed respectively, based on which the topological characteristics are analysed. The results show that the spatiotemporal interaction networks exhibit high regional connectivity and node interdependence, suggesting the presence of a small-world phenomenon.

1. Introduction

Shared bicycle is a new form of transportation and can accurately record users' riding information in real time, providing a large amount of effective mobility data. In recent years, with the rapid development of bike share as well as urbanization, shared bicycling has emerged as a preferred mode of transportation for short-distance travel among citizens (Griffin and Sener, 2016), especially for the first and last mile transit and short commutes. The interaction patterns generated shared bicycles traveled among spatial units during different time periods can be explored through constructing complex networks and mining the characteristics embedded in the networks, providing an available way to exploring human movement patterns in urban areas (Yao et al., 2019).

Currently, a significant portion of research in this field focus on the analysis of stationary shared bicycles, which presents certain limitations such as suboptimal data quality resulting from data sampling deviations and information gaps (Wan, 2020). This is because the stationary shared bicycling requires borrow or return shared bicycles to a specific location. In contrast, the dockless shared bicycling system presents real-time display position with its own positioning system, which can be parked and placed everywhere (Chen et al., 2020, 2022; Orvin and Fatmi, 2021). In this study, we explore the spatiotemporal interaction patterns through building dockless shared bicycling networks, which is critical for modelling human mobility patterns, aiding urban planning, urban traffic management as well as promoting the urban sustainable development (Xu et al., 2019).

Leveraging a dataset comprising over 20 million dockless shared bicycle orders from the City of Shenzhen, China, this study employs the patterns embedded in the spatiotemporal interaction network based on a number of indicators, such as the average degree of nodes, the average clustering coefficient, closeness centrality, and betweenness centrality. The objective of the study is to obtain a comprehensive understanding of the spatiotemporal patterns underlying shared bicycle usage.

The structure of this paper is organized as follows. Section 2 introduces the study area and the data used in this study. Section 3 presents the methodology adopted for analysing the spatiotemporal interaction patterns of shared bicycling networks. Section 4 analyses the results, and some conclusions are drawn in Section 5.

2. Study Area and Data

2.1 Study Area

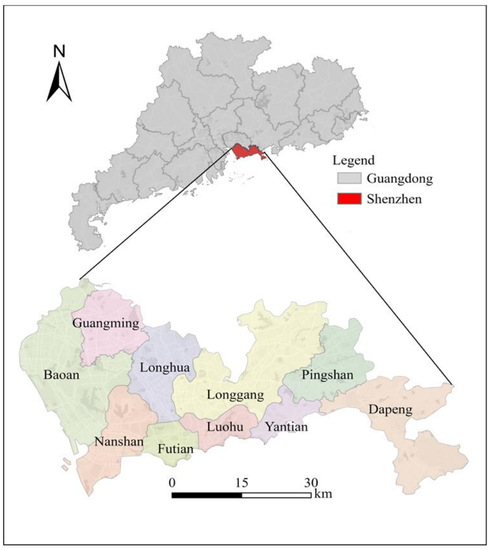

Figure 1. Overview of the study area

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This study selected the City of Shenzhen, Guangdong Province, China as the research area, which is located between 113°46′~114°37′ *E* and 22°27′~22°52′ *N*. As shown in Figure 1, Shenzhen is bounded by Daya Bay and Dapeng Bay to the east, the Pearl River estuary and Lingdingyang to the west, and shares borders with Hong Kong, Dongguan, and Huizhou. The research area encompasses a total land area of 1997.47 square kilometers and owns nine administrative districts, including Bao'an, Nanshan, Futian, Luohu, Yantian, Longhua, Longgang, Pingshan, Guangming, and Dapeng Districts.

2.2 Datasets

The study incorporates two primary datasets, namely administrative boundary data and shared bicycle data. The administrative boundary data of the City of Shenzhen was sourced from the Shenzhen Geographic Information Public Service Platform (http://www.szgeoinfo.com.cn). The shared bicycle order data of the City of Shenzhen was obtained from the Shenzhen Municipal Government Data Open Platform (https://opendata.sz.gov.cn). The shared bicycle order data specifically pertains to the dockless shared bicycle orders in Shenzhen, ranging from March 30 to April 13, 2021, constituting a two-week duration. Using the data API provided by the platform, a web crawler was developed to collect the dockless shared bicycle order data, yielding a vast dataset of approximately 20.22 million entries. The acquired shared bicycle order data encompasses various attributes including user ID, company ID, timestamps of the start and end of the journey, and the latitude and longitude coordinates for both the starting point (denoted as 'O') and the endpoint (denoted as 'D').

3. Methodology

Figure 2 illustrates an overview of the methods and processes employed in this work, including research data and preprocessing, spatial and temporal partition, spatiotemporal interaction networks construction, and analysis of network characteristics.

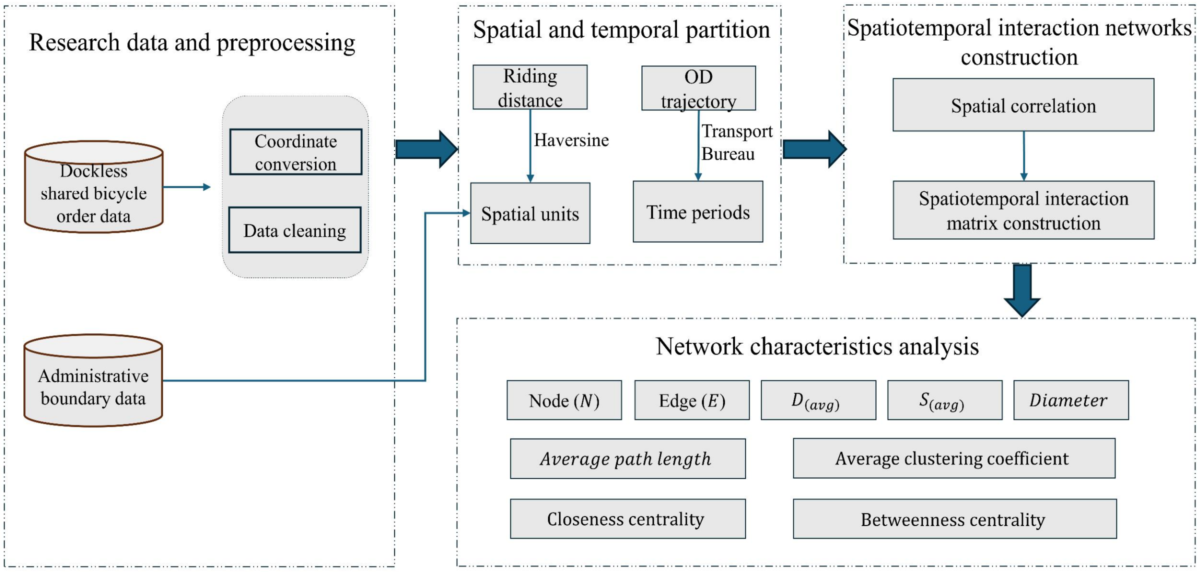

Figure 2. The overall study workflow

3.1 Spatial and Temporal Partition

In order to enhance the reliability and accuracy as well as remove the redundancy of the data, a series of pre-processing steps were employed. The details are as follows.

(1). Coordinate conversion: The original coordinate system of administrative boundary data is BD09, which is commonly used in Baidu map. In order to facilitate the follow-up experimental research, we unified the coordinate system as the WGS84 coordinate system for the administrative boundary data.

(2). Data cleaning: The Euclidean distance of shared bike orders in the plane was computed using the *Transbigdata* toolkit (https://transbigdata.readthedocs.io) in *Python* language, based on which the orders exhibiting abnormal riding distance greater than three kilometres were removed from the dataset (Xie, 2021). In addition, the data with blank values in the fields such as timestamps and coordinates, and the data points outside the study area were also removed.

Through the above pre-processing steps, approximately 8% of the shared bicycle order data was eliminated. The remaining valid data were used for the study to provide the basis for subsequent experiments.

3.1.1 Spatial Partition: As the construction of spatiotemporal interaction networks of shared bicycling highly relies on the size of spatial units. The variations in spatial unit sizes can significantly influence the topological characteristics of the composed networks. In this paper, we determined the size of spatial units through calculating the cycling distance of shared bicycles and using the probability density distribution of the cycling distance as an indicator. The *Haversine* distance based on the spherical model was used to calculate the riding distance of the shared bicycle, since it is based on the spherical cosine function transformation, effectively addressing discrepancies in distance calculation for points situated closer together and ensuring heightened accuracy in computations (Maria et al., 2020). The *Haversine* distance is computed as follows.

$$hav\left(\frac{d}{r}\right) = hav(\varphi_2 - \varphi_1) + \cos(\varphi_1)\cos(\varphi_2)\,hav(\lambda_2 - \lambda_1) \qquad (1)$$

$$hav(\theta) = sin^2\left(\frac{\theta}{2}\right) = \frac{1-\cos(\theta)}{2} \quad (2)$$

In the formula, hav is the Haversine function, d denotes the riding distance of shared bicycles, φ_1 and φ_2 represent the latitude of the starting point and the end point of the shared bicycle order, λ_1 and λ_2 represent the longitude of the starting point and the end point of the shared bicycle order, and r denotes the radius of the earth.

Once the size of spatial units was determined, a spatial grid partition was conducted through partitioning the research area into a number of equal-size grids.

3.1.2 Temporal Partition: The determination of time periods in this study was determined by referring to the transportation policy issued by the Traffic Police Department of Shenzhen Local Public Security Bureau in 2023 (http://szjj.sz.gov.cn). The study mainly divided the time into five periods, i.e., weekday morning peak (7am-9am), weekday daytime off-peak (9am-5:30pm), weekday evening peak (5:30pm-7:30pm), weekday nighttime off-peak (7:30pm-7am), and weekends (all-day period), which are shown in Table 1.

Time periods	Description
Weekday morning peak	7am-9am
Weekday daytime off-peak -	9am-5:30pm
Weekday evening peak	5:30pm-7:30pm
Weekday nighttime off-peak	7:30pm-7am
Weekends	all-day period

Table 1. Time periods and description

3.2 Spatiotemporal Interaction Networks Construction

The complex network theory was adopted for spatiotemporal interaction networks construction, since it can illustrate the spatiotemporal interaction patterns among different spatial units through regarding the spatial units and their interaction as nodes and edges, respectively in the bike-sharing system in a comprehensive way. The Spatiotemporal interaction networks of shared bicycles can be regarded as an edge-weighted graph network $G = (N, E, W)$ (Wu et al., 2020; Gomez-Gardenes et al., 2013; Liu et al., 2021), where three basic elements including node (N), edge (E), and edge weight (W) are required. As the partitioned spatial units refer to the equal-size grids, the centroids of the partitioned spatial units were used as nodes, the flows of shared bicycles were used as edges, and number of shared bicycle rides were used as weight to construct the spatiotemporal interaction network of shared bicycles in different time periods. The details of building the interactive network of shared bicycle spacetime are as follows.

3.2.1 Spatial Correlation: We employed the *sjoin* function in the *Geopandas* library (https://geopandas.org) to generate the origin and destination vector points based on latitude and longitude from the pre-processed bicycle data. The spatial associations were established between the OD points and the partitioned spatial unit dataset for the City of Shenzhen. This ensured that OD points were attached with the corresponding spatial unit ID. The grid IDs corresponding to the start point and end point were assigned to the shared bicycle order data, resulting in the bicycle order data enriched with spatial unit information.

3.2.2 Spatiotemporal Interaction Matrix Construction: The starting point O, the ending point D, and the weights expressed in terms of the frequency of shared bicycle rides were extracted in different time periods in order to compose the spatiotemporal travel matrix. The *network* or *igraph* algorithms in Python language were used to model the spatiotemporal travel matrix for the following analysis.

3.3 Network Characteristics Analysis

In order to analyse the characteristics of the spatiotemporal interaction networks, the following indicators were involved for complex network analysis in this study (Xu et al., 2023).

(1). Node (*N*): The centroids of starting unit and ending unit places of bicycle sharing rides.

(2). Edge (*E*): The connection between the starting node and the end node of the shared bicycle ride.

(3). Average degree ($D_{(avg)}$): The number of edges connected to a node in the network is called the *Degree* of the node. The average degree of all nodes in a network is called the average degree of the network.

$$D_{(avg)} = \frac{\sum_{i=1}^{N} E_i}{N} \quad (3)$$

The $D_{(avg)}$ represents the average degree of the node i in the spatiotemporal interaction network and E_i represents the number of edges of the node i.

(4). Average strength ($S_{(avg)}$): The average weighted degree of nodes is the average strength, which is computed as follows.

$$S_{(avg)} = \frac{\sum_{i=1}^{N} W_i}{N} \quad (4)$$

The $S_{(avg)}$ represents the average strength of the spatial interaction network node i and W_i represents the weight of the edge of node i.

(5). Network diameter (*Diameter*): The maximum distance between any two connected nodes in the spatiotemporal interaction network represents the network diameter, which is calculated as follows.

$$Diameter = max_{i \neq j} d_{(i,j)} \quad (5)$$

The $d_{(i,j)}$ represents the distance between node i and node j.

(6). Average path length: The average value of all distances between two nodes refers to average path length, which can reflect the degree of separation between nodes and can be computed using Equation 6. The higher the value is, the more dispersed the network nodes are.

$$Average\ path\ length = \frac{2}{N(N-1)} \sum_{i \neq j} d_{(i,j)} \quad (6)$$

(7). Average clustering coefficient (*ACC*): The ratio of the number of connections around the node to the number of possible connections of the node is defined as the clustering coefficient C_i, which is used to measure the degree of aggregation of nodes. The *ACC* can be computed using Equation (7) and (8).

$$C_i = \frac{2E_i}{D_i(D_i - 1)} \tag{7}$$

$$\langle C \rangle = \frac{1}{N}\sum_{i=1}^{N} C_i \tag{8}$$

In spatiotemporal interaction networks, a higher *ACC* indicates that the spatial units are more closely connected to each other. Otherwise, the spatial units in the network are more dispersed.

(8). Closeness centrality: The closeness centrality of a node is the average distances from the node to all other nodes and represents the propagation efficiency of the connection, which reflects the proximity of a node to other nodes. It can be calculated as follows.

$$Closeness_i = \frac{N}{\sum_j d_{(j,i)}} \tag{9}$$

(9). Betweenness centrality (*Betweenness$_i$*): It refers to the number of times a node appears on the shortest path, reflecting the degree of control and dependence of the node on other nodes, which can be calculated as follows:

$$Betweenness_i = \sum_{m \neq n \neq i} \frac{\sigma_{mn(i)}}{\sigma_{mn}} \tag{10}$$

The $\sigma_{mn(i)}$ denotes the number of the shortest paths of node *m* and node *n* passing through node *i* in the spatiotemporal interaction network and σ_{mn} denotes the sum of the number of shortest paths from node *m* to node *n*.

4. Results and Analysis

4.1 Partitioned Spatial Units

The optimal value for spatial unit partition was determined through investigating the probability density distribution of riding distance, as shown in Figure 3. The distance of each shared bicycle ride was calculated according to Equation (1).

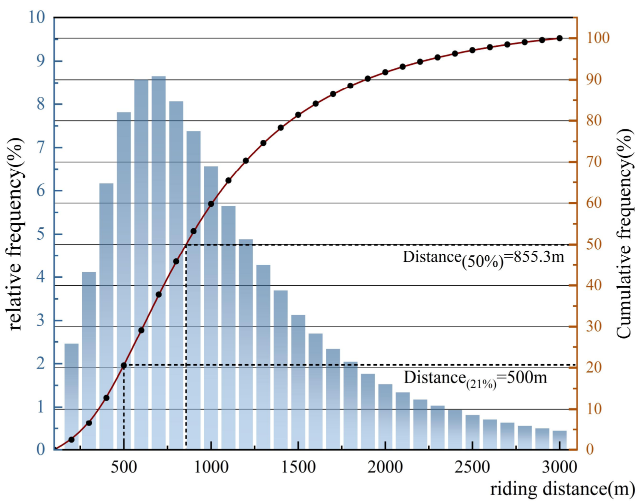

Figure 3. The probability density distribution of riding distances

The histogram in Figure 3 demonstrates the frequency of riding shared bicycles in different distance intervals. Overall, there are relatively more short-distance rides on shared bicycles, with the highest relative frequency of riding distances around 700 meters. In other words, the majority of shared bicycles have riding distances near 700 meters. The average riding distance of bicycles was computed as 999.2 meters. The riding distance of half of the orders are more than 855 meters, three-quarters of them are more than 500 meters, and the vast majority are more than 250 meters. In order to make the start point and end point occurring in different spatial units to explore the spatiotemporal interaction patterns, we initially selected 250 meters and 500 meters as the partition length of spatial units. Through dividing the research area with 500m × 500m grid and 250m × 250m grid in ArcGIS, it revealed that the division did not show great difference. In order to reduce redundancy, 500 meters was finally selected as the length for dividing the spatial unites in Shenzhen. A total of 8,298 spatial units were finally obtained.

4.2 Spatiotemporal Interaction Networks

According to the principles of network construction elaborated in Section 3.2, five spatiotemporal interaction networks were constructed in five difference time periods using the bicycle sharing data in Shenzhen. The constructed spatiotemporal interaction networks are shown in Figure 4.

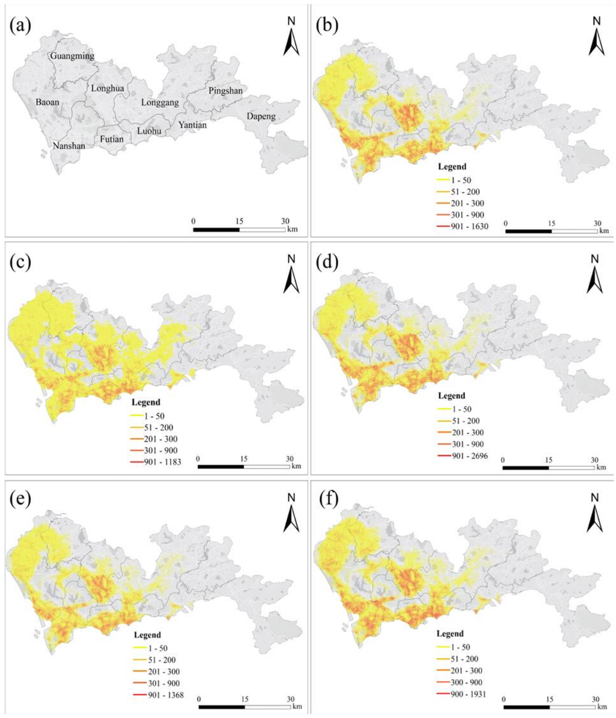

Figure 4. The spatiotemporal interaction networks of bicycle sharing in the City of Shenzhen, China. (a) The admin boundary map;(b) Weekday morning peak; (c) Weekday daytime off-peak;(d) Weekday evening peak; (e) Weekday nighttime off-peak; (f) Weekends

The yellow color in the figure represents the weight, namely the number of shared bicycle rides. The darker the color, the more frequently the rides in those areas. It shows that the frequency of shared bicycle flow in all time periods are the highest in Longhua District. For instance, during the evening rush hours on weekdays, the flow frequency of shared bicycles is the highest, indicating the number of citizens using shared bicycles during this period is the largest. Comparing with Guangming, Bao'an, Nanshan, Futian and Luohu districts, there are fewer bike-sharing rides in Pingshan, Yantian and Dapeng districts. As indicated by the announcement of the Shenzhen Municipal Transportation Bureau (http://jtys.sz.gov.cn), the number of shared bicycles in Dapeng, Yantian and Pingshan districts was 3,600, 6,600 and 15,300 respectively by the end of 2023, which were less than other districts. The potential reason behind such phenomenon is that Dapeng, Yantian and Pingshan are relatively far from downtown and most tourism industries and high-tech industries locate there, and the bike companies don't deploy many bikes and there are fewer shared bicycles provided for citizens and tourists in order to keep costs and benefits balance. On the weekends, most of the riding activities take place in Guangming, Bao 'an, Nanshan, Luohu and Longhua districts.

4.3 Network Characteristics

Based on the constructed spatiotemporal interaction networks of shared bicycles in each period, we computed nine indicators for exploring the network characteristics, including the number of nodes, the number of edges, the average degree of nodes, the average strength of nodes, network diameter, average path length, average clustering coefficient, closeness centrality and betweenness centrality. The calculation results are shown in Table 2.

	Weekdays				Weekends all-day period
	Morning peak (7am-9am)	Daytime off-peak (9am-5:30pm)	Evening peak (5:30pm-7:30pm)	Nighttime off-peak (7:30pm-7am)	
N	3467	3594	3588	3574	3802
E	98019	96711	108573	101948	147507
$D_{(avg)}$	56.54	53.82	60.52	57.48	77.59
$S_{(avg)}$	1152.59	932.35	1014.42	863.49	1831.23
Diameter	32	30	28	31	28
Average path length	9.93	9.72	9.64	9.72	9.22
Average clustering coefficient	0.43	0.46	0.45	0.46	0.50
Closeness centrality	0.097	0.098	0.103	0.105	0.116
Betweenness centrality	20933.75	22733.19	20875.09	21491.36	20985.65

Table 2. The statistics of network attributes during the study periods

As shown in Table 2, the number of nodes (*N*) and the number of edges (*E*) of the spatiotemporal interaction network increased significantly during the peak hours of the weekday evening, indicating that people ride shared bikes more frequently during weekday evening hours. This is possibly because weekday evening peak hours are at the end of the workday and peak time, riders have enough time for shared bike use. Moreover, the prevalence of traffic congestion during the evening peak hour highly motivates individuals to opt for shared bicycles as their preferred mode of transportation.

In terms of network diameter and average path length, the value of the morning peak of weekdays are significantly higher than those of other time periods, illustrating that people use shared bicycles to ride far away from other time periods during the morning peak of the working day, and the origin and destination of the ride are relatively scattered, while other periods of cycling are more concentrated. Since the values of the average path length in the spatiotemporal interaction networks are around 10 among the large number of nodes, it is likely that people usually take part in local activities around by shared bicycles, which can be called "small world" phenomenon.

The highest average clustering coefficient and closeness centrality are both found on weekends, suggesting that community activities are more closely connected and concentrated on weekends than weekdays. In terms of betweenness centrality, the values of betweenness centrality were relatively high for all time periods, which suggests that the spatiotemporal interaction networks hold a high degree of regional connectivity dependency among the spatial units.

5. Conclusion

This study facilitates the construction of spatiotemporal interaction network using dockless bike-sharing data based on the complex network theory, enabling the investigation of patterns using nine indicators, including the number of nodes, the number of edges, average degree of nodes, average strength of nodes, network diameter, average path length, average clustering coefficient, closeness centrality and betweenness centrality. A case study conducted in Shenzhen City, China, reveals that Longhua District emerges as the most frequent area for bike-sharing usage. The travel distance tends to be longer during weekday mornings, while the travel distances in other time periods are relatively shorter, which shows homogeneous usage patterns in space. On weekends, travel distances tend to be shorter and more clustered, particularly in the Guangming, Bao'an, Nanshan, Luohu, and Longhua districts. The spatiotemporal interaction network illustrates a high level of regional interconnectedness and reliance, showcasing the small-world phenomenon. These findings offer insights for urban transport authorities, bike-sharing companies, and residents to enhance urban mobility.

Despite the findings obtained in this study, there exists certain space for improvement. The analysis was based on two-week bike-sharing order data due to the challenge of accessing long-term data, leading to potentially incomplete insights. In the future, more spatiotemporal dynamics of dockless bike-sharing system can be investigated for comparison given more data can be collected from either traffic management departments or bike-sharing providers.

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