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Research Article

Analysis of the Relationship between Dockless Bicycle-Sharing and the Metro: Connection, Competition, and Complementation

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Dockless bicycle-sharing (DLBS) is one of the novel transportation modes emerging in recent years. As a newly arisen mode, dockless bicycle-sharing inevitably has influence on the existing components of the public transportation system, especially the metro system. A large number of scholars have explored the integration relationship between the two. However, through the evaluation and quantification of the dockless bicycle-sharing data and the metro automatic fare collection data, we find that the relationship between the two is not unique. Based on the location of origin and destination, the travel duration, and the travel distance, the dockless bicycle-sharing trips closely related to the metro were identified and categorized into three different temporal-spatial relationships: competition trips, connection trips, and complementation trips. Three indicators were proposed to characterize the relationship between the two systems. A case study was carried out in Shanghai, China. The proposed method was applied to investigate when, where, and to what extent the dockless bicycle-sharing trips compete with, integrate with, and complement the metro. The results show that dockless bicycle-sharing mainly integrates with and complements the metro. It is where the dockless bicycle-sharing trip takes place and the trip significantly determines its relationship with the metro. The findings provide significant implications regarding the design and management of dockless bicycle-sharing and the metro.

1. Introduction

Since the end of the 2000s, bicycle-sharing systems have been rapidly developed and adopted worldwide [1] and have become an important component of the public transportation system for short-distance travel in cities. The Internet-based dockless bicycle-sharing (DLBS) systems are particularly well received by the public and universally recognized by the market [2]. The DLBS enhances urban mobility, promotes the accessibility of public transport, and reduces the use of motorized transport [3]. As a newly arisen mode, DLBS inevitably has influence on the public transit systems, including the bus system and the metro. The DLBS can positively or negatively impact public transit meaning it can be either a collaborator or a competitor for public transit. [4] As a solution to last-mile problems, the first- and last-mile connections to and from the metro have gotten wide attention. In Shanghai, there are 1.07 million DLBS trips on average whose origins or destinations are associated with metro stations, accounting for about 34% of the daily DLBS trips [5]. Statistics in Shenzhen [6] also show that 47% of the DLBS trips are used to reach metro stations. However, the relationship between the DLBS and the metro is mixed and complex. Except for the collaboration (connection), the other relationship, such as the complementation and competition relationship between the two systems have not been well substantiated and qualified.

The lack of data integration and the lack of integrated analytic skills are the two reasons for the research gaps in deciphering the relationship between the two systems. The understanding of the relationship between the two systems requires the traceability of the entire journey with multiple transportation modes. Some existing studies collected data based on traditional inquiry surveys which cannot fully trace

the entire travel process. Some literature applied large-scale datasets from the two systems, respectively, but lacked the ability to incorporate the different data sources.

To fill the research gaps in the existing literature, this study introduces the DLBS data and the metro automatic fare collection (AFC) data to evaluate and quantify the relationship between DLBS and the metro. Based on the location of origin and destination of DLBS trips, the DLBS travel duration, and the DLBS travel distance, five scenarios are proposed to establish the connection between DLBS and the metro and enable to analyze the travel patterns of the two systems as a whole. DLBS trips closely related to the metro are identified and categorized into three groups: competition trips, connection trips, and complementation trips. To investigate when, where, and to what extent the DLBS trips compete with, integrate with, and complement the metro, three indicators are proposed to characterize the relationship between the two systems. Finally, the proposed method is carried out in the case study of Shanghai, China. Several significant implications regarding the design and management of DLBS and the metro are summarized from the results.

The contributions of this paper are as follows:

(i) A method is proposed to identify the relationship between DLBS and the metro based on the data integration of the large-scale dataset collected from the two systems, respectively. A set of indicators is proposed to integrate the travel patterns of the two systems and quantify the relationship between the two systems.

(ii) Through the example verification of Shanghai, it is confirmed that in addition to the connection, there are also overlapping (competition relationship) and supplement (complementation relationship) between dockless bicycle-sharing and the Metro.

The remainder of this paper is organized as follows. Section 2 presents a review of the related works. Section 3 introduces the multi-source dataset. Section 4 presents the methodology of the relationship identification between the two systems. Section 5 presents the case study in Shanghai, China. Finally, conclusions and future directions are given.

2. Related Works

In this section, the related work is summarized in three aspects, which are the DLBS usage characteristics analysis, the relationship between the BSS and the public transit system, the relationship between the DLBS and the metro.

2.1. The DLBS Usage Characteristics Analysis. Sufficient studies have analyzed the characteristics of the usage of bicycle-sharing. Compared to docked bicycle-sharing, DLBS have no fixed stations and are usually private, start-up, and venture capital projects. Most DLBS users are mobile Internet users and most DLBS units are equipped with GPS devices for easy redistribution and maintenance. [7] Many studies [8–12] have proposed a series of methods to analyze the temporal and spatial heterogeneity of DLBS usage characteristics. For example, Zhuang et al. [8] applied cluster analysis to a DLBS dataset to automatically identify typical cyclic patterns in the spatiotemporal dimension. Song et al. [9] analyzed the demand of BSs and used global and local Moran's I index and community detection to model the spatiotemporal dynamics of circular mobility. Bao et al. [11] applied clustering methods and text mining-based potential dirichlet assignment methods to identify DLBS trip distributions and trip purposes. Zhang et al. [13] studied the temporal and spatial heterogeneity from the perspective of penetration theory, and the results revealed the oversupply of bikes in urban centers and the imbalance between supply and demand on a larger scale. In addition, a series of studies have analyzed the factors influencing usage characteristics, showing that conditions such as land use, socio-economics, population density, roadway designs, transportation facilities, cycling infrastructures, weather (including temperature, humidity, air quality) [3, 14–18], and changes in human mobility due to the COVID-19 pandemic [19–21] can have an impact on the mobility characteristics of bike-sharing (either DBS or DLBS).

2.2. The Relationship between BS and the Public Transit. With the gradual increase of research on the regularity of bicycle-sharing movement, the relationship between bicycle-sharing and the public transit is being further explored. Fuller D pointed out that bicycle-sharing is associated with transportation mode transfer in his research on the impact of BS on collision accidents in Canada [22]. Zhang [23] investigated the relationship between the frequency of public transportation use and the probability and frequency of BS use using survey data from the United States. The results showed that for each unit increase in the frequency of public transportation use, the probability of using BS increased by 4.0% and the frequency of using BS increased by 1.4%. Zhu et al. [24] surveyed public bicycle users in Shanghai and found that most users used shared bicycles to replace their original public transportation. Martin et al. [25] focused on Washington, DC and Minneapolis bicycle-sharing users' travel behavior. They found that in low-density urban areas, bike-sharing users used it more to connect to public transportation services; in high-density urban centers, more bike-sharing trips were used to replace public transportation. Fishman [26] surveyed bikeshare users in five cities, Melbourne, Brisbane, Washington D.C., London, and Minneapolis, and ultimately found a substitution relationship between bikeshare, walking, and public transportation. Fuller et al. [27] used telephone survey data to investigate bikeshare use in Montreal and found that bikeshare had a substitution effect on public transportation. Campbell [28] developed a two-difference model using data from transit and bikeshare systems to test the substitution relationship between BS and transit in New York City. Kong et al. [29] deciphered the relationship between bicycle-sharing and public transit and divided them into three categories: Modal substitution, integration, and complementation, which have great reference value.

2.3. The Relationship between BS and the Metro. In practical applications, bicycle-sharing is one of the important ways to solve the "last-mile" problem of public transportation; therefore, in recent years, a wealth of research on the relationship between bike-sharing and metro systems has focused on the integration between the two. Bocker et al. [30] found that when other factors such as distance, elevation, travel time, and urban form are consistent, bike-sharing traffic will be significantly higher if the trip origin and destination are related to a rail transit station. Part of the literature [10, 18] mined the impact of bike-sharing on rail transit stations and used hierarchical clustering to cluster rail transit stations into morning and evening peak bike-gathering stations, morning peak bike-gathering stations, and evening peak bike-gathering stations. Yu et al. [31] used bike-sharing data and subway travel data to extract indicators and used a confidence ellipse approach to make an analysis of the service area of shared bicycles around metro stations. Yan et al. [32] extracted shared bicycle operation order data related to Shanghai rail transit line 9, visualized and analyzed the differences in the usage patterns of dockless shared bicycles around the metro on weekdays and holidays, and revealed the characteristics of the service area of dockless shared bicycles around the metro. In addition, some studies have investigated the factors influencing the integration between bike-sharing and metro. For example, Muhammad et al. [33] investigated and analyzed user preferences for last-mile feeder using a mixed choice model and found the influence of user preferences on metro-BS integration. Hu et al. [34] fitted a set of generalized additive models considering marginal nonlinear interactions and examined the relationship between the external environment (including land use, sociodemographics, roadway designs, transportation facilities, metro station features, and DLBS operator features) and the activity characteristics of metro-integrated bicycles. And, some bike-sharing systems that primarily serve city centers (e.g., the bike-sharing system in downtown Dublin) or serve suburban areas (e.g., the system in Jiangning District, Nanjing, China) show integration relationships with the metro as users need to commute between central and suburban areas. [35–37].

Apart from integration, other relationships between bike-sharing and metro have been less studied. Ma Knaap [38] compared the use of bicycle-sharing and metro in Washington, DC in 2010 and 2015, and found that for metro stations in the downtown area, there are bicycle-sharing stations within a 1/4 mile (about 402 m) range, which reduces the number of metro travels, and for the metro stations in the fringe area, the stations with bicycle-sharing increase the metro passenger flow. This demonstrates the substitution and complementarity of bike-sharing for the metro.

2.4. Literature Summary. In summary, the research on the relationship between bike-sharing systems and public transportation: bike-sharing and public transit (bus) can be summarized as substitution, integration, and complementation. In contrast, research on the relationship between dockless bicycle-sharing systems (DLBS) and subways focuses on integration, and there is a gap in research on other relationships between the two. In addition, it can be seen from the previous studies that most of the studies are based on questionnaire surveys, studying the relationship between bicycle-sharing and public transportation and trying to find out the influence factors. However, traditional survey methods have many drawbacks. With the development of information and communication technology, multi-source big data contain a wealth of crowd movement information and has the characteristics of large samples and low cost [39], which can provide more effective tools for bicycle-sharing-related research. Therefore, to fill the research gap, this study aims to fuse the travel data of the two systems, quantify the relationship between the DLBS system and the metro, and investigate the spatiotemporal patterns of DLBS trips that replace, integrate, and complement the metro.

3. Datasets

3.1. The Dockless Bicycle-Sharing Data. In this study, the DLBS data were provided by Shanghai Transportation Commission, including dockless bicycles registered through all formal channels in Shanghai from May 1st to May 12th, 2019. It is composed of more than 1.7 million bicycles and generates 1.07 million average daily trips. The information of each data includes the bicycle ID, lock status, timestamps, and longitude and latitude coordinates. In addition, most of the data processing in this paper is supported by the Python package TransBigData. [40].

Several filters were applied to the data before further data processing. First, the OD information was extracted. The data were generated when the lock was opened and closed, so by which record the starting and ending positions of each single bicycle travel. The change of lock status of each bicycle with the same ID can correspond to the beginning and end of a riding order. Thus, the OD information of each order can be extracted. And, through the calculation and sorting, the bicycle ID, the duration and distance of travel, the departure and arrival time, and the departure and arrival position are explicitly recorded in the dataset. Therefore, by monitoring the DLBS data, the DLBS system can be turned into a virtual sensor network for sensing mobility in the city. Second, there existed some outliers with too short or long travel time. In this study, trips with durations less than 1 min or greater than 120 min were identified as outliers and were dropped. Third, to reflect the actual demand of DLBS, May 6th (Monday) and 12th (Sunday) were selected as two typical days to represent the travel demand on weekdays and weekends. After data cleaning and data filtering, 1,086277 and 853237 DLBS trips were obtained on May 6th and 12th, respectively (Figure 1).

3.2. Metro Automatic Fare Collection Data. The metro automatic fare collection (AFC) data were collected from the metro system in Shanghai from May 1st to May 12th, 2019. Shanghai metro network is composed of 17 lines and 387 stations, with an average daily ridership of 10.6 million. The

metro AFC system stores the inbound and outbound records, and the metro ridership at the station-to-station level. The metro AFC data used in this paper provide the information of hourly passenger flows in 387 metro stations, including the metro line ID, the metro station name, hours of the day, the hourly inbound passenger flow, and the hourly outbound passenger flow.

Figure 2 shows the temporal variation in hourly ridership of the metro network on May 6th and 12th. The temporal variation of hourly ridership shows significant differences between weekdays and weekends. On weekdays, the temporal variation presents obvious characteristics of morning and evening peak within a day. While on weekends, the temporal distribution of ridership tends to be relatively uniform.

4. Methodology

4.1. Methodology Framework. Figure 3 shows the methodology framework of this study. The DLBS data, metro GIS data, and metro AFC data were used to evaluate and analyze the relationship between the DLBS system and the metro system. The methodology can be briefly described as follows:

(1) Spatial matching. The origin and destination of each DLBS trip are extracted from the DLBS data. With the help of metro GIS data, spatial matching is carried out to search and match the origin and destination with their nearest metro stations.

(2) Buffer area segmentation. To distinguish the DLBS demand around metro stations, a data-driven method is proposed to segment the coverage area of metro stations.

(3) DLBS trip classification. To establish the connection between DLBS and the metro, DLBS trips closely related to the metro are identified based on the location of DLBS origin and destination, the DLBS travel duration, and the DLBS travel distance. According to the relationship with the metro, the identified trips are categorized into three groups: competition trips, connection trips, and complementation trips.

(4) DLBS-metro Relationship Characterization. To analyze the travel patterns of the two systems as a whole, three indicators are proposed to characterize the relationship between the two systems, including the share of connection around the metro station, the intensity of competition along the metro route, and the demand of complementation outside the metro coverage area.

4.2. Identification of Relationship between DLBS and the Metro. The large-scale dataset of DLBS trips applied in this study enables to collect the travel information of DLBS trips with smaller bias and less labor intensity. By comparing and fusing the two types of data, the relationship between their travel demands at the spatial and temporal levels can be found and thus their relationship can be explored.

First, trips with a relationship to the metro are identified, the distance between DLBS origin/destination and metro station is the main factor to be considered. In previous studies, most scholars often take a definitional approach to identify the interchange trips: a bike-sharing trip is defined as an interchange trip if its origin or destination is located in a catchment area around a metro station. Some literature defines the radius of the catchment area as 300 m [41, 42] or 500 m [5, 31, 43, 44], and the smaller the radius, the higher the percentage of interchange trips within the catchment area [45]. In a face-to-face questionnaire survey conducted by Li et al. [46] on the trip purpose of bike-sharing users around the metro, most respondents (>75%) indicated that their bike-sharing trips were related to the metro when the origin or destination was located within a 500 m buffer zone of a Shanghai metro station. Zhao et al. [47] proposed a data matching method based on association rules and verified it. The results show that 573 pairs of smart cards are matched within 300 m around the subway station, and the accuracy is 100%. Therefore, we can assume that by judging the distance between DLBS origin/destination and metro station, we can judge the relationships of most trips.

Then, the time of DLBS trip occurrence and DLBS travel distance are considered to make it closer to the real situation and thus increase the accuracy. Finally, the trips are categorized into three modes and they are defined as follows:

(1) Competition: Competition refers to the situation in which DLBS is used as a substitute for the metro. Within the service time of the metro system, if both the origin and the destination of DLBS trip are close to metro stations, the user is supposed to take the metro to complete the trip without too much walking, waiting, and transferring. In this case, DLBS is considered an alternative to the metro.

(2) Connection: Connection refers to the situation where the metro is the core of the entire journey, and DLBS is used to get access to the metro. In this case, both the spatial relationship and the temporal relationship between DLBS and the metro should be considered. The spatial relationship between the two systems requires that either the origin or destination of the DLBS trip should be close to metro stations. For temporal relationship, the DLBS trip should arrive shortly before the departing time of metro trip or depart shortly after the arriving time of metro trip. In addition, the duration of the DLBS trip should not be too long.

(3) Complementation: Complementation refers to the situation where DLBS is used in areas with insufficient metro coverage. In other words, if either the origin or destination, or both, of the DLBS trip is far away from metro stations, DLBS is considered a complementary mode to the metro.

Based on the definition of relationships between the two systems, a three-step method is proposed to distinguish the relationship between DLBS and the metro.

4.2.1. Spatial Matching. The first step is spatial matching. To identify the relationship between DLBS and the metro, it is important to understand the spatial relationship between the
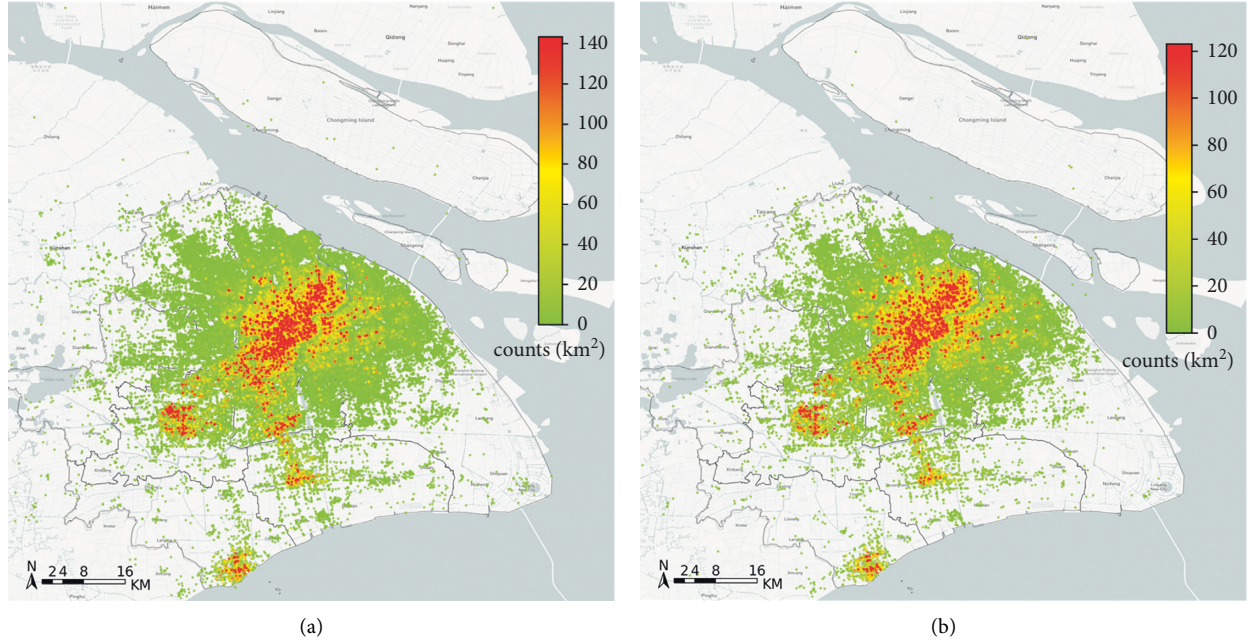
(a) (b)

Figure 1: Spatial distribution of DLBS trips' origin point (unit: counts/km²). (a) May 6th (Weekday). (b) May 12th (Weekend).
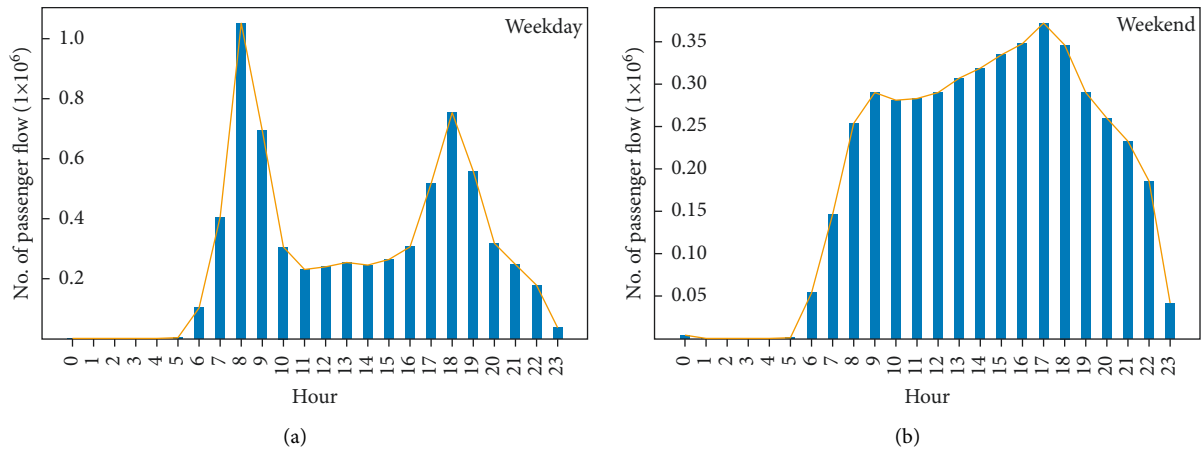

(a) (b)

Figure 2: The temporal variation in hourly ridership of the metro network. (a) May 6th (Weekday). (b) May 12th (Weekend).

origin and destination of each DLBS trip and the metro stations. To improve the speed of matching, this paper uses The KDtree algorithm to search the origin and destination of DLBS trips, and matches them with the nearest metro stations.

(1) Extract the departure and arrival information of each DLBS trip from the DLBS data, and determine the geographic coordinates of the origin and destination.

(2) Divide the space of the metro stations, establish a spatial index, and perform a binary tree search on the origin and destination of each DLBS trip to find the nearest metro station.

(3) Calculate the closest distance between the origin or destination and the metro station.

$$dist = 2 \arcsin \sqrt{\sin^2 \frac{y_1 - y_2}{2} + \cos\ y_1 \times\ \cos\ y_2 \times\ \sin^2 \frac{x_1 - x_2}{2}}$$
$$\times\ 6378.137,$$

(1)

where x_1, y_1 denote the longitude and latitude of DLBS trip origin or destination, x_2, y_2 denote the longitude and latitude of the nearest metro station, and $di\ st$ represents the distance measured by the kilometer.

4.2.2. Buffer Area Segmentation. Buffer area segmentation is applied to divide the coverage area of the metro system. Previous studies mostly generated the buffer area of public

transportation based on questionnaire surveys or empirical experience, which cannot accurately reflect the buffer relationship between bicycle-sharing and public transportation. Hawas et al. [48] proposed that a place can be considered to be covered by public transportation, if it gets access to a public transit station within a comfortable walking distance. Wu [49] determined this comfortable walking distance to be 400 meters. Jin et al. [50] introduced 100 meters as another threshold to assist the analysis of the relationship between Uber and public transit. Kong et al. [29] proposed "traffic coverage" to measure the spatial distribution of public transportation services, and divided the urban space into three regions based on the threshold of 100 meters and 400 meters. And, Hu et al. [43] proposed a spatial network density-based method to determine the optimal size of the parking ring (buffer area) based on large volume of bike-sharing travel data in determining the bike-and-ride (BnR) trips, where the size of the parking ring is measured by the network distance and its boundary is obtained from the concave surface of all accessible nodes, which can better reflect the real cycling scenario. (Figure 3)

This study proposes a data-driven method for buffer area segmentation based on large-scale DLBS data. Given the origin and destination of DLBS trips, the distances between the origin or destination and the nearest metro station can be obtained. Applying Kernel Density Estimation to find the estimated probability density function of distance, the spatial relationship between DLBS and the metro can be visualized in Figure 4.

Most DLBS trips start or end within two kilometers away from metro stations. It can be seen from Figure 4 that there are two peaks in the probability density function. The first peak is around 80–100 meters, the second peak is around 400–600 meters, and a trough can be found around 240–280 meters. The first peak is likely to associate with the bicycle parking facilities around the metro stations. The second peak is the outcome of the origins or destinations of users' first-mile or last-mile trips. The trough between the two peaks represents the weakened spatial agglomeration of DLBS demand. It indicates that 260 meters can be used as a threshold to distinguish the DLBS demand around metro stations.

In addition, to distinguish whether the DLBS trip is associated with the metro, set the second threshold. Without considering the connection transportation, the service range of the metro station is that people can walk (750 m) to the entrance and exit of the station within 10 minutes, and it should be the superposition of the reasonable reachable range of multiple single starting points [51]. Therefore, considering the distribution of multiple entrances and exits of the metro station and surrounding roads, it is set as 1000 m. The two thresholds divide the coverage area around a metro station into three parts:

(1) Near metro station area (Area A): Buffer areas within 260 meters away from the metro stations. Area A is within a few minutes' walk from the metro stations. If the DLBS trip starts or ends in Area A, the user is likely to pick up the bicycle after alighting the train or drop off the bicycle before boarding. 21.20% of the weekday DLBS trips and 23.23% of the weekend DLBS trips start or end in Area A around the metro stations.

(2) Metro radiation area (Area B): Buffer areas within the range of 260–1000 meters away from the metro stations. Area B is the transition area; it lies in the coverage area of the metro station but outside the comfortable walking distance which indicates the service coverage of the subway system. 53.45% of the weekday DLBS trips and 59.78% of the weekend DLBS trips start or end in Area B around the metro stations.

(3) Far metro station area (Area C): Areas outside the buffer areas, more than 1000 meters away from the metro stations. Trips in these areas will be unrelated to the metro system, meaning that when the OD of the trip is all far from the metro, the bike becomes a transportation option.

4.2.3. DLBS Trip Classification.

Allocating the origin and destination of each DLBS trip to the areas as mentioned above, the cases shown in Table 1 are proposed to represent the relationship between DLBS and metro, which can contain all valid DLBS trip orders in the dataset.

According to the spatial distribution of the seven ODs obtained in the above table, to further improve the accuracy of the relationship classification, attention should be paid to the time of trip occurrence, and orders that exceed the Shanghai metro's operation hours (5:25 to 23:00) should be excluded from the potential connection and substitution relationships and categorized in the supplementary relationships. Finally, combined with the DLBS trip distances, five key scenarios are proposed to represent the relationship between DLBS and the metro which are shown in Figure 5.

Scenario 1. Short-distance DLBS trips between Area A and Area B/C

In Scenario 1, Considering that the distance of DLBS trips for connection should not be too long [4], we mainly focus on the DLBS trip shorter than or equal to 2 kilometers. The DLBS trips either start or end very close to the metro stations. DLBS is used as the first-mile/last-mile connection of the metro. In this case, DLBS trips are categorized as connection trips.

Scenario 2. DLBS trips between Area A around different metro stations

In Scenario 2, both the origin and destination of DLBS trips are located very close to the metro stations. The DLBS trips in Scenario 2 are likely to replace the trips formerly made by metro. In this case, DLBS trips are categorized as competition trips.

Scenario 3. DLBS trips between Area B around the same metro station

In Scenario 3, there is a certain distance between the metro station and the origin and destination of DLBS trips.
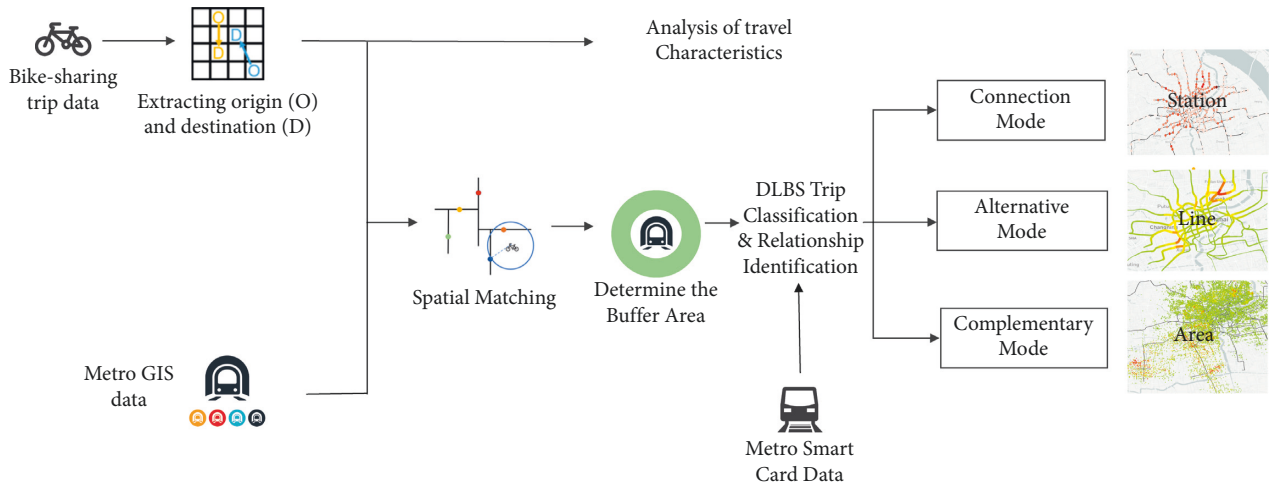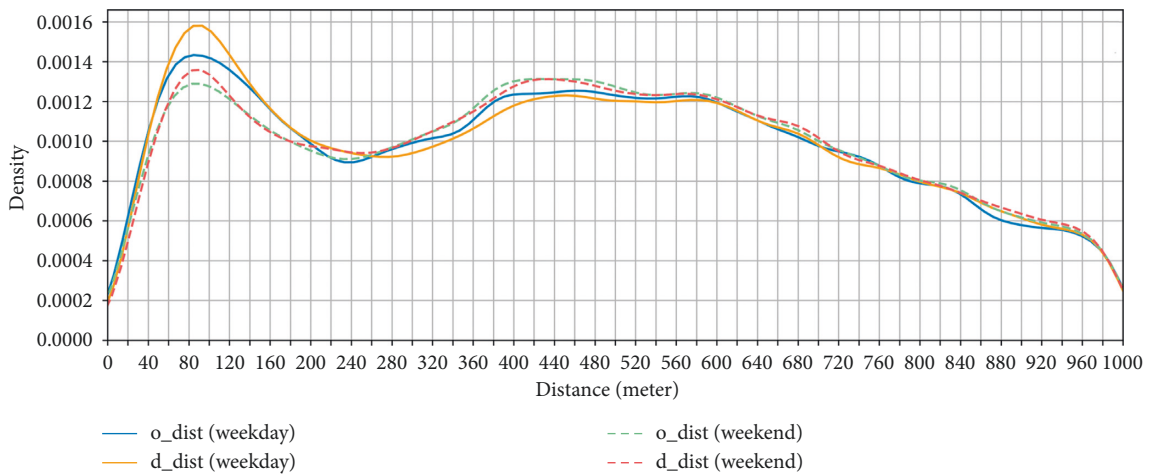
Figure 3: Methodology framework.

Figure 4: The estimated probability density function of the distance between the origin or destination of DLBS trips and metro stations.

Table 1: Spatial relationship between DLBS trips OD and buffer zone.

Cases	Description	Relationship
Case 1	Only one of O and D is in area A	Potential connection
Case 2	Area A to area A around different metro stations	Potential competition
Case 3	Area B to area B around different metro stations	Potential competition
Case 4	Area A to area A around the same metro station	Excluded due to short-distance
Case 5	Area B to area B around the same metro station	Complementation
Case 6	Area B/C to area C/B	Complementation
Case 7	Area C to area C	No relation

Are located very close to the metro stations. In this case, since both the origin and destination are in the Area B around the same metro station, DLBS is a complementary mode to the metro. Therefore, DLBS trips are labelled as complementation trips.

Scenario 4. DLBS trips between Area B around different metro stations

In Scenario 4, users prefer to use DLBS to complete the entire journey between Area B around different metro

stations. Both the origin and destination of DLBS trips are a certain distance away from the metro stations. Compared with the metro, DLBS provides a convenient, inexpensive, and door-to-door service. In this case, DLBS is more likely to be considered as a substitute for the metro. Therefore, DLBS trips are categorized as competition trips.

Scenario 5. DLBS trips between Area B and Area C

In Scenario 5, either the origin or destination of DLBS trips is outside the coverage of the metro. These DLBS trips
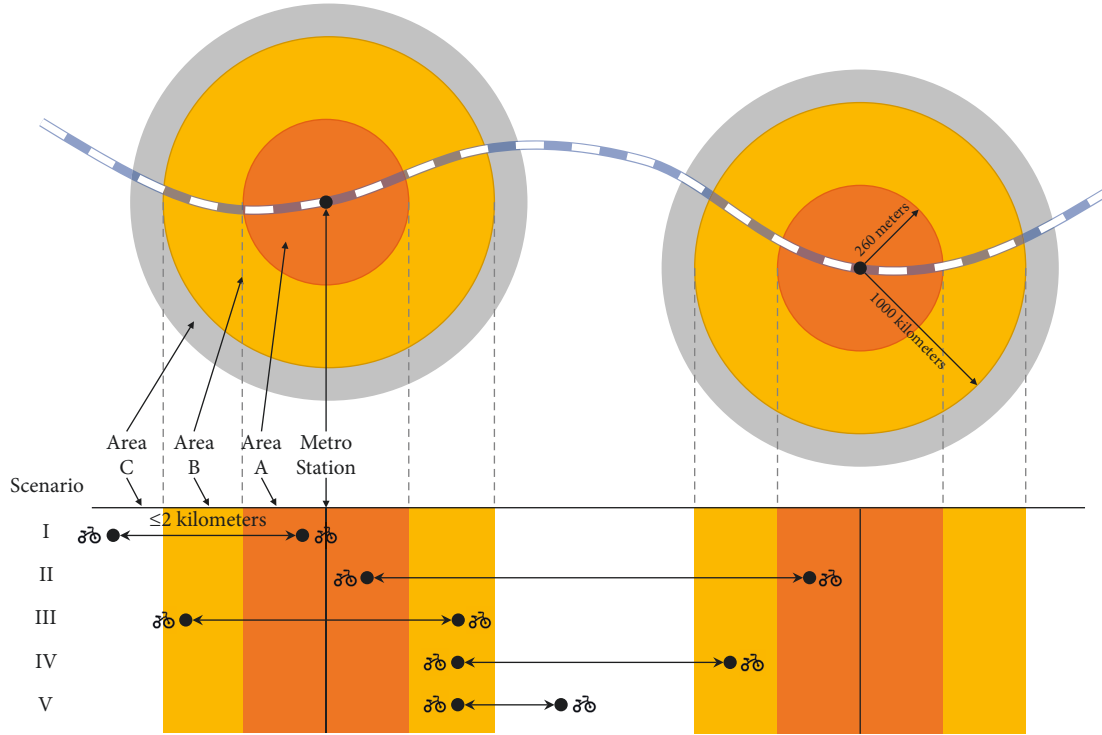
FIGURE 5: Illustration of the five scenarios.

cannot replace or be combined with the rail transit. In this case, DLBS acts as a complementary mode to enhance the urban mobility in areas with insufficient metro coverage. In this case, DLBS trips are labelled as complementation trips.

4.2.4. DLBS-Metro Relationship Characterization. The five scenarios mentioned above establish the connection between DLBS and the metro and enable to analyze the travel patterns of the two systems as a whole. Three indicators are proposed to characterize the relationship between DLBS and the metro. The three indicators correspond to the travel patterns of three types of DLBS trips, respectively, including the share of connection around the metro stations, the intensity of competition along the metro lines, and the demand of complementation outside the metro coverage area.

(1) The share of connection. The share of connection refers to the share of DLBS connection in the passengers of the metro station. This indicator is proposed to analyze the DLBS connection demand of metro passengers at the station level. Given a time window Δt, let A_i denote the Area A around the metro station i, in the DLBS data, there are o_i DLBS trips departing from A_i and d_i trips arriving at A_i. Meanwhile, there are o_i' boarding passengers in the metro station i and d_i' alighting passengers in this station. Then, the share of connection at metro station i can be calculated as :

$$S_i = \frac{d_i + o_i}{o_i' + d_i'}. \tag{2}$$

(2) The Intensity of Competition. The intensity of competition refers to the metro passenger flow that has been diverted to DLBS. This indicator is proposed to restore the distribution of diverted metro passenger flow from the O-D demand of DLBS competition trips. Given a time window Δt, let A_i and B_i denote the Area A, B, respectively, around the metro station i, in the DLBS data, there are n_{ij} DLBS competition trips from A_i to A_j and m_{ij} competition trips from B_i to B_j. Assuming that all the DLBS competition trips were formerly made by metro, the diverted metro O-D demand from station i to station j can be calculated as (3):

$$r_{ij} = n_{ij} + m_{ij}. \tag{3}$$

Based on the diverted metro O-D matrix $R = (r_{ij})$, traffic assignment is carried out to allocate trips between metro stations to the metro network. For the two adjacent metro stations i, j, the intensity of competition I_{ij} refers to the allocated passenger flow in the segment from station i to j, that is, the segment passenger flow diverted by DLBS.

(3) The Demand of Complementation. The demand of complementation refers to the number of DLBS complementation trips in the areas with insufficient metro coverage. This indicator is proposed to analyze the demand of DLBS complementation trips at the area level. Given a time window Δt and a 500 m × 500 m grid covering the study area, there are u_i DLBS competition trips departing from the grid cell i and w_i trips arriving at this cell. Then, the demand of complementation trips in the grid cell i can be calculated as:

$$D_i = u_i + w_i. \tag{4}$$

5. Results and Discussion

5.1. Travel Characteristics of DLBS. The travel characteristics of DLBS are analyzed based on the travel duration, the travel distance and the turnover rate obtained from DLBS data.

As for the travel duration, the average travel duration is 13.12 minutes on May 6th and 11.05 minutes on May 12th. The average travel duration on working days is slightly longer than that on weekends.

As for the travel distance, the average travel distance is 1250.9 meters on May 6th and 1199.3 meters on May 12th. The estimated probability density function of DLBS travel distance is shown in Figure 6. There is no great difference in travel distance between weekdays and weekends. The distribution of travel distance has an obvious peak and fat tail. The DLBS travel distance is mostly smaller than 5000 meters and reaches a peak at around 600–700 meters (Figure 7).

The daily turnover rate of bicycles can reflect the overall situation of bicycle resource usage. The average turnover rate of active bicycles is 5.68 on May 6th and 4.97 on May 12th. However, according to the statistics published by the government, the average turnover rate of all the shared bicycles in Shanghai was 1.1 in 2019. The dramatic difference indicates that there are a large number of inactive bicycles in the city. The horizontal axis of the bar chart in Figure 7 represents the daily turnover rate, while the vertical axis is the frequency, showing the frequency distribution of the different daily turnover rates of active bikes in the dataset. The figure shows that most of the bike-sharing bikes have less than ten completed orders per day. And, compared with the turnover rate on weekends, there are more bicycles used for more than three times on weekdays.

5.2. Analysis of the Relationship between DLBS and the Metro

5.2.1. General Patterns. Given the preprocessed DLBS data on May 6th and 12th, 2019, the relationship between DLBS and the metro was identified, and the proportion of different kinds of relationship was illustrated in Figure 8. The share of three kinds of trips is significantly different between weekend trips and weekday trips. Figure 8(a) shows that the connection trips dominate weekday trips, followed by complementation trips and competition trips. Figure 8(b) shows that the share of complementation trips is the largest in weekend trips, followed by connection trips and competition trips. The share of connection trips and complementation trips are considerable in both weekdays and weekends, accounting for about 75% of DLBS trips. The results show that DLBS mainly integrates with and complements the metro.

5.2.2. Temporal Patterns. In addition to the difference between weekend and weekday trips, DLBS trips in different times of day might also be different. Figure 9 illustrates the number of connection, complementation, and competition trips in different times of day, and Figure 10 illustrates the temporal variation of the share of different kinds of trips.

Several observations can be made from the two figures. First, the hourly patterns of DLBS trips are clearly different between weekday and weekend. All the three kinds of DLBS trips show sharp morning and evening peak on weekdays, whereas the weekend patterns are featured with relatively smooth summits. These results suggest that all the three kinds of DLBS trips have a large percentage of commuting trips, whereas the purposes of weekend trips are more diversified. Second, the temporal patterns illustrated in Figures 8 and 9 indicate that commute plays an important role in the composition of DLBS trips. Connection trips dominate DLBS trips during the morning and evening peak on weekdays, the share of which ranges from 40% to 48%. DLBS has been widely accepted as the seamless access to metro stations and widely used in the peak commuting hours. Complementation trips make up the majority of DLBS trips during the off-peak hours of weekdays and the whole weekends. The differences in the share of connection trips and complementation trips between peak hours and off-peak hours indicate that commute as a trip purpose might be a significant determining factor in the relationship between DLBS and the metro.

5.2.3. Spatial Patterns. Figure 11 shows the DLBS connection shares around Shanghai metro stations, using the color and size of the dots to indicate the proportion of passengers entering and exiting the station at that metro station who chose DLBS for their connection. The results resonate with our previous findings that the share of connection trips is much larger on weekdays. The mean value of the share of connection is 7.5% on May 6th and 5.4% on May 12th.

From the spatial distribution of the share of connection in Figure 11, significant spatial heterogeneity can be observed. The value of the share of connection is smaller in the city center and suburban areas. The city center is covered with dense public transportation networks and well-developed metro networks. There barely exists the demand of medium- or long-distance connection in the city center. As for the suburban areas, the insufficient DLBS supply cannot meet all the demand of connection with the metro.

Fuxing Island Station, Tongji University Station, Guoquan Road Station, Sanmen Road Station, and Wuwei Road Station are the five metro stations with the highest share of connection. The five stations and other stations with high share of connection have some common features that they are located between city center and suburban areas and surrounded with residential districts or industrial districts.

These findings imply that for connection trips, the public transportation networks, the supply of DLBS service, and the building environment around the metro stations are determining factors (Figure 11).

The intensity of competition along the metro segments is calculated and illustrated in Figure 12. The color and the width of lines represent the intensity of competition with DLBS, that is, the segment passenger flow diverted by DLBS.

The spatial distribution of the intensity of competition on weekdays coincides with that on weekends. Most of the metro sections with a large intensity of competition are the sections before the first transferring stations from the
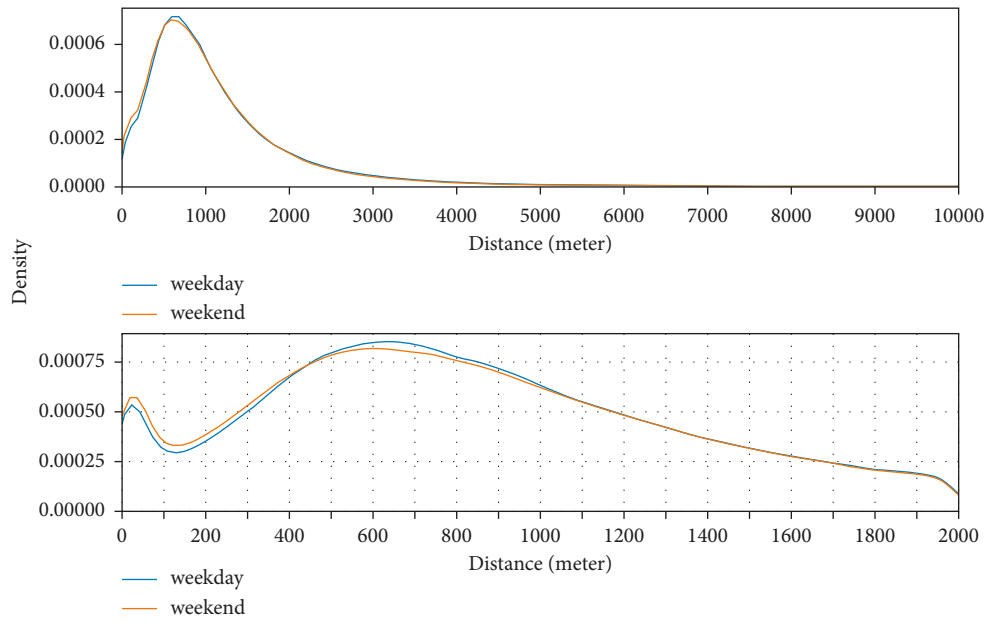
FIGURE 6: The estimated probability density function of DLBS travel distance.
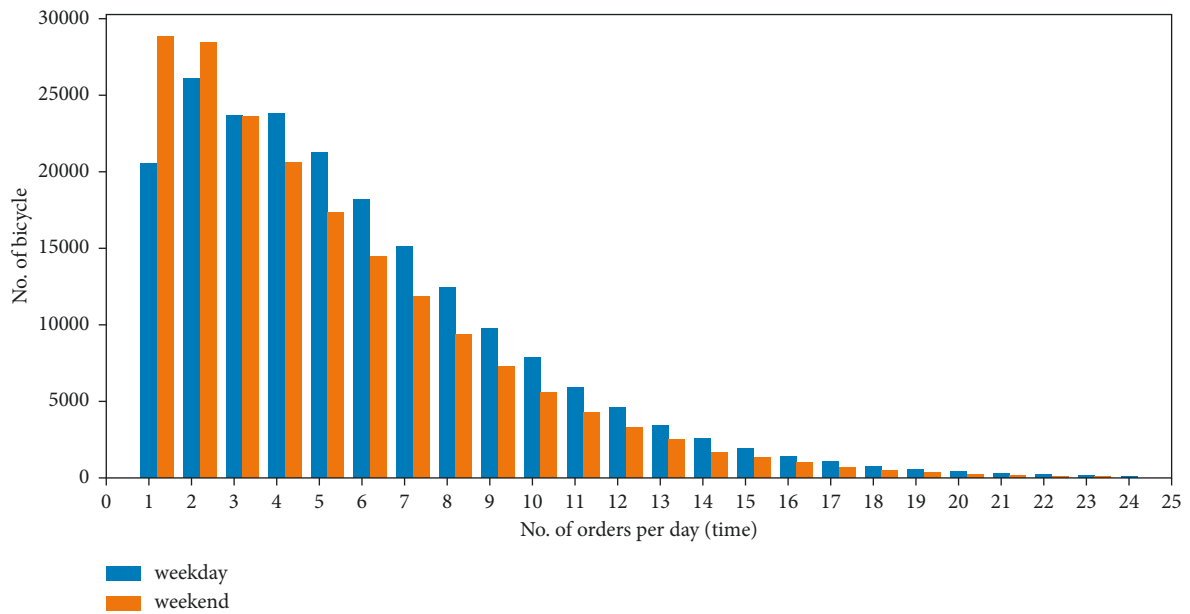

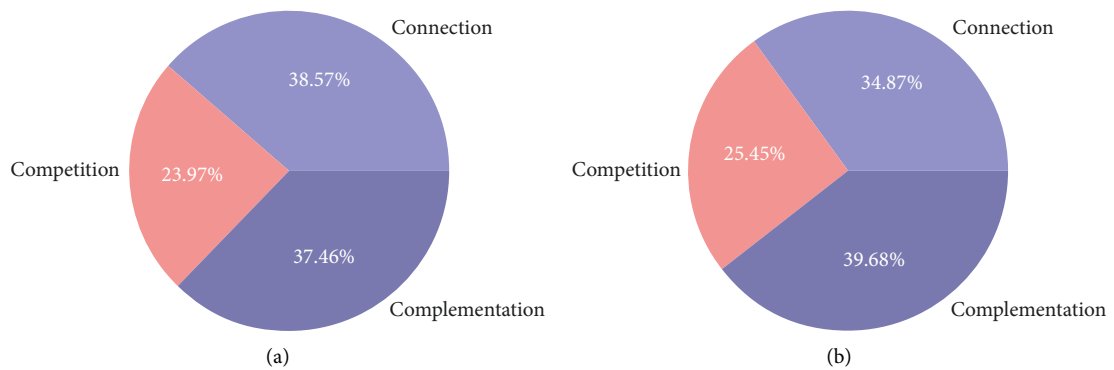FIGURE 7: The distribution of the daily turnover rate of active bicycles.

FIGURE 8: The share of connection, complementation, and competition trips. (a) Weekday. (b) Weekend.
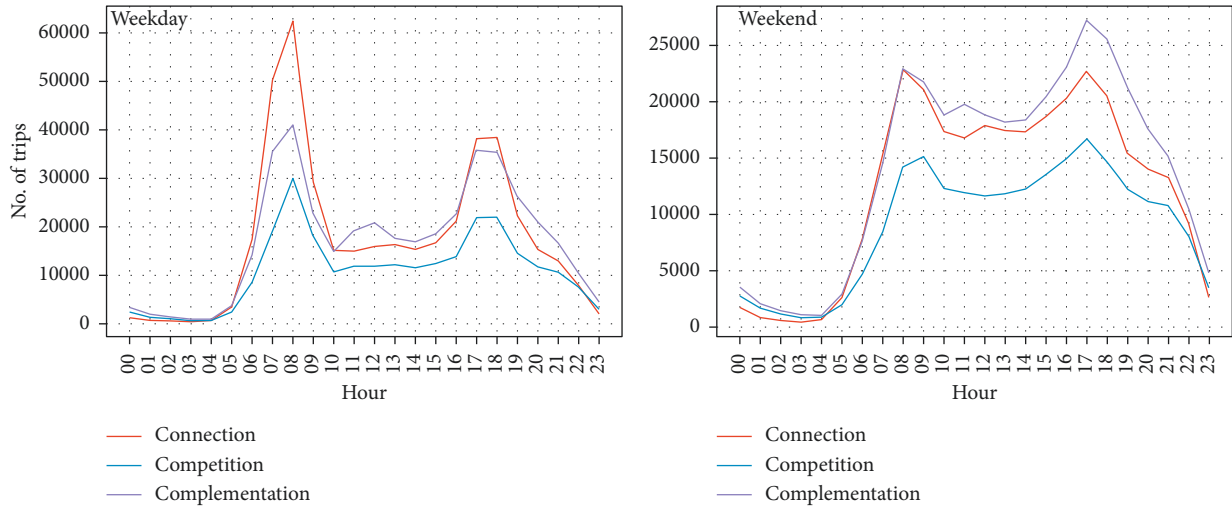
FIGURE 9: The hourly variation of the number of connection, complementation, and competition trips.
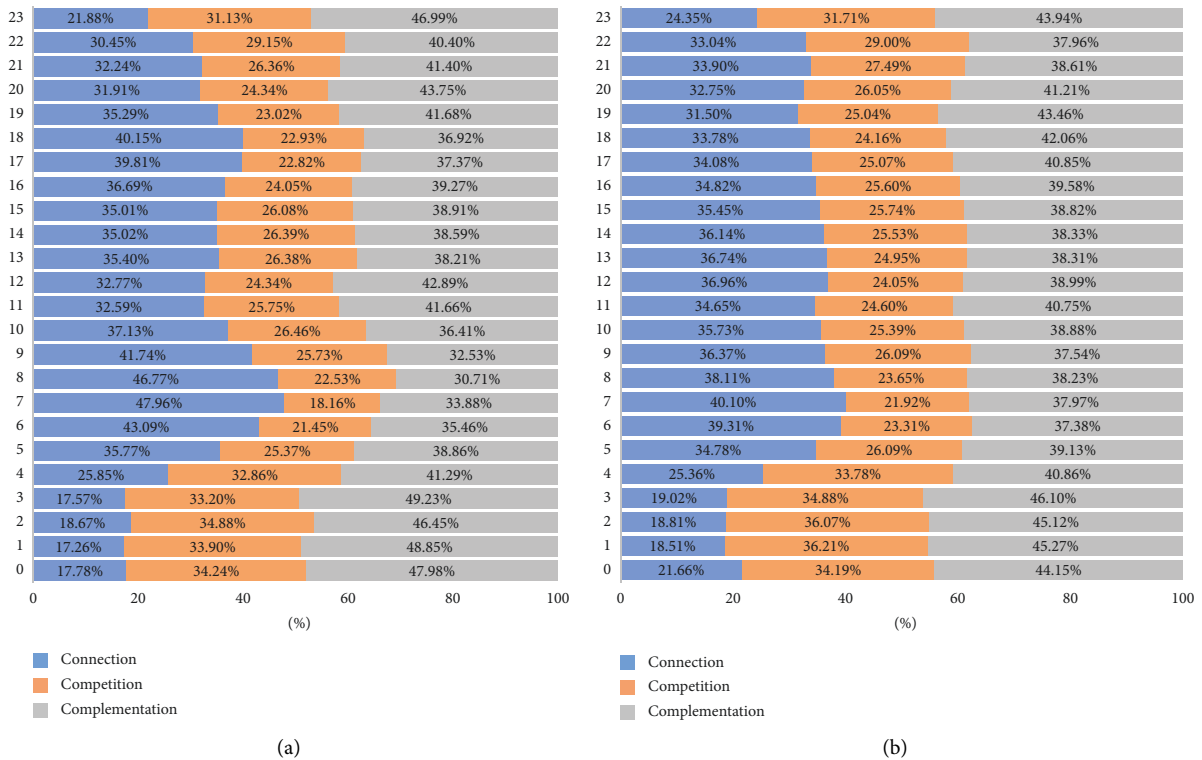

FIGURE 10: The hourly variation of the share of connection, complementation, and competition trips. (a) Weekday. (b) Weekend.

suburban areas to the city center. These sections are usually the maximum section of passenger flow of the metro lines.

These results suggest that for competition trips, what matters is not how far a place is away from the city center, but rather how crowded the metro is. DLBS is regarded as an alternative solution to escape from the crowded metro.

With the rapid development of the city and the continuous expansion of urban lands, DLBS can be a useful tool to complement public transportation networks in areas with insufficient metro coverage. The demand of complementation is calculated and plotted in Figure 13.

As can be seen from the figure, complementation trips are more widely distributed on weekends, which might be because of the more diversified travel demand on weekends. The areas with huge demand of complementation trips are mainly located around the terminal stations in the suburban end of Metro Line 1, 5, 9, and 12. In these areas, the public transportation is not well-developed and short in supply. Preference has been given to DLBS to complete the medium- or long-distance trips. As a supplementary to public transportation services, DLBS enhances the mobility in the area and promotes the accessibility of public transportation networks.
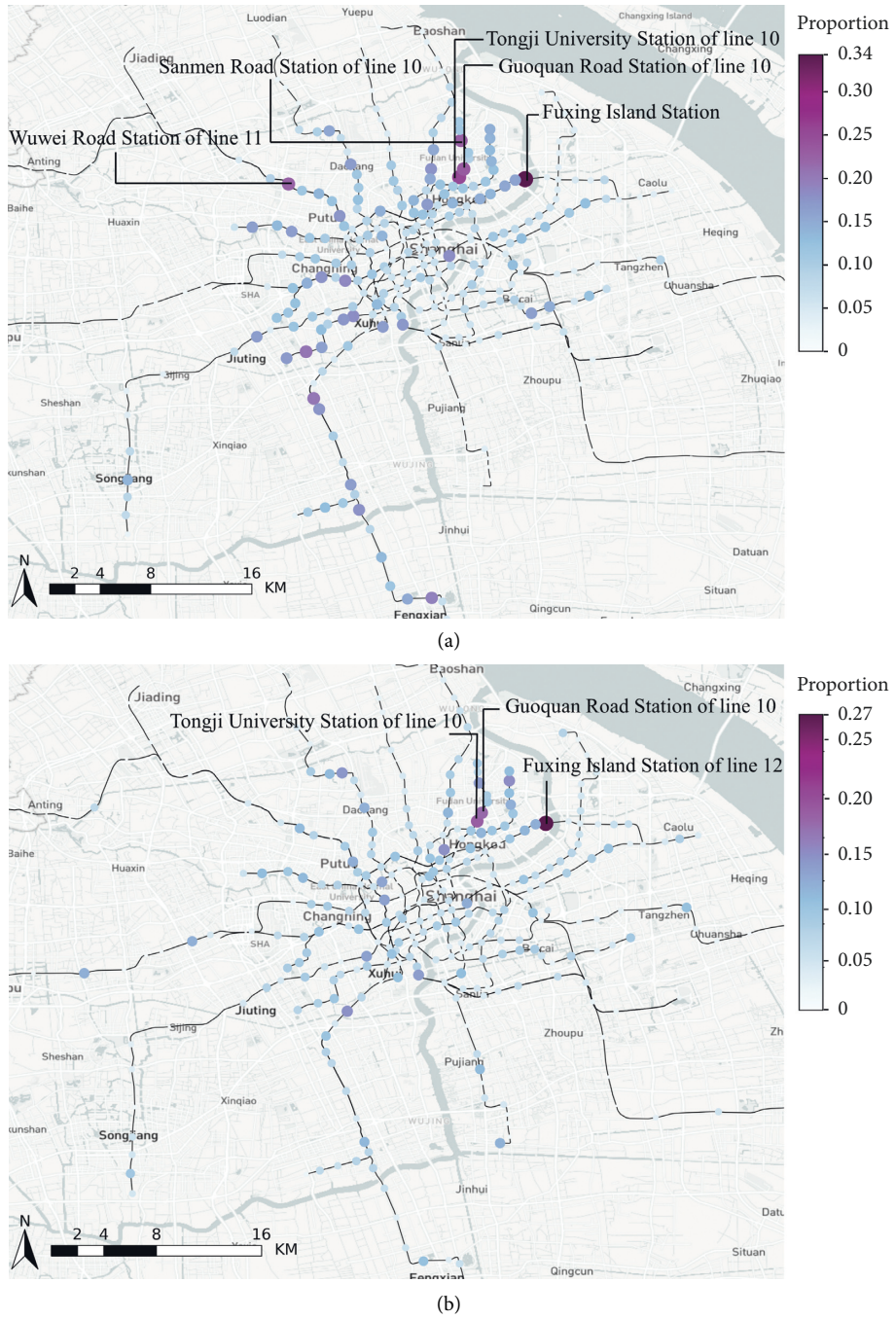
(a)

(b)

Figure 11: The share of connection around the metro stations. (a) Weekday. (b) Weekend.
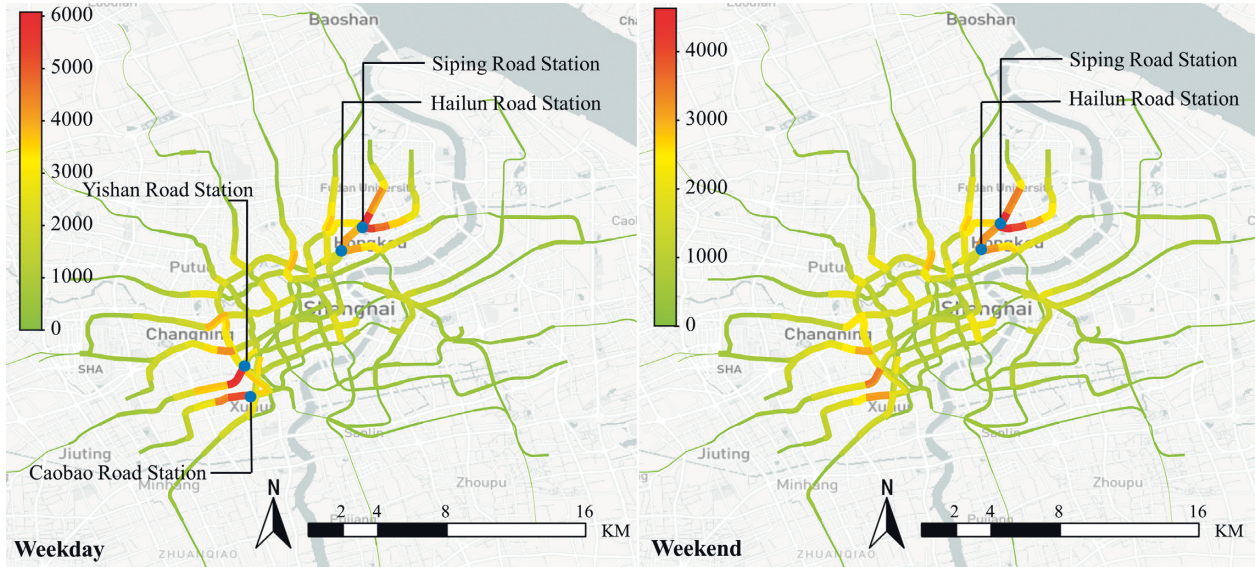
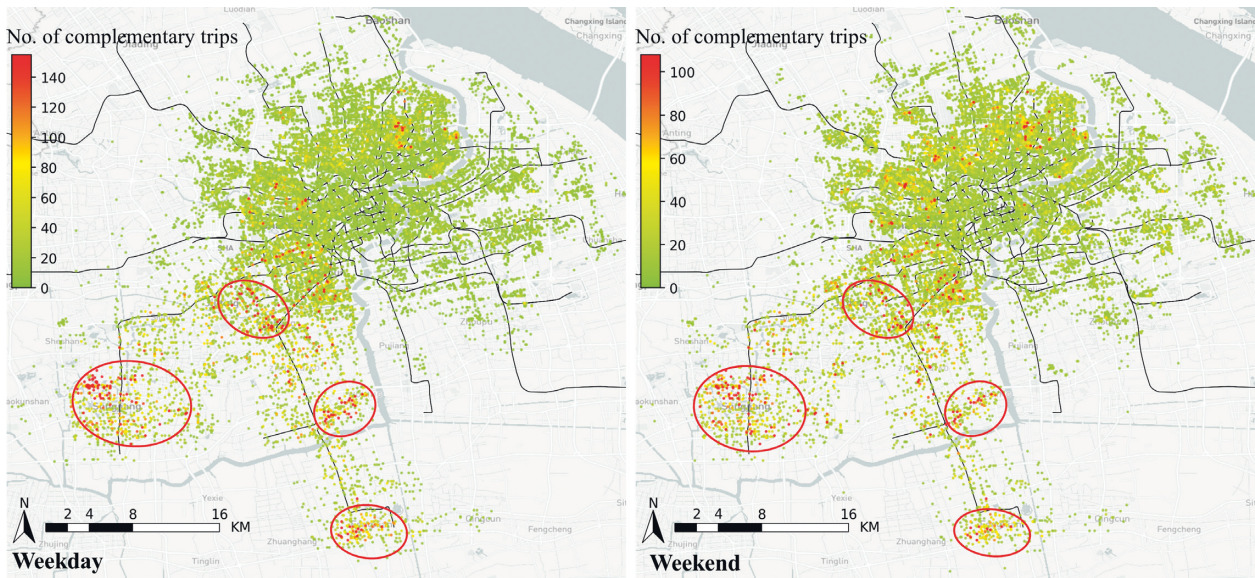FIGURE 12: The intensity of competition along the metro segments.

FIGURE 13: The demand of complementation trips.

6. Conclusions and Future Directions

In recent years, DLBS has gradually been warmly welcomed by the public. In the urban transportation system, as an environment-friendly short-distance shared travel mode, DLBS enhances the mobility of the city and promotes the accessibility of the transportation network. The development of new transportation modes will inevitably have an impact on the existing modes, especially the metro system. This study applies the DLBS data and the metro AFC data to quantify the internal relationship and the interaction between the two systems. Using the large-scale dataset collected from the two systems, respectively, a method is proposed to identify the relationship between the two

systems. Three indicators are proposed to integrate the travel patterns of the two systems and quantify the relationship between the two systems.

   (i) The relationship between DLBS and the metro can be defined as competition, connection, and complementation. DLBS trips mainly integrate with and complement the metro.

   (ii) Corresponding to the three kinds of relationships, the relationship between the two systems can be characterized by the share of connection around the metro stations, the intensity of competition along the metro lines, and the demand for complementation outside the metro coverage area.

The findings from the case study of Shanghai suggest that both where the dockless bicycle-sharing trip takes place and when the trip happens significantly determine its relationship with the metro. Commute as a trip purpose might be a significant determining factor in the relationship between DLBS and the metro.

Our study provides a framework for analyzing the relationship between DLBS and other transportation modes. According to the research conclusion, the accuracy of the two systems can be recommended for the construction and management of stations, lines, and regions to improve the operation efficiency and service level of the two systems, promote the reasonable integration and development between the two systems, and effectively promote the overall optimization of the urban transportation system. We believe that not only the proposed methods but also the problem-solving ideas and management framework apply to other cities with different conditions.

However, this paper only uses longitude and latitude coordinates, which may not reflect street layout or terrain, in the distance calculation of shared single vehicle travel, which has certain limitations. In addition, it does not know more about the relationship between DLBS companies and the planning entity. It should continue to be discussed in future research.

Meanwhile, based on the spatiotemporal heterogeneity that we found for different categories of DBL trips, deeper research can continue, for example, what are the potential underlying mechanisms that present these spatiotemporal patterns. Hu et al. [43] fitted a set of generalized additive models considering marginal nonlinear interactions to the association between metro-related trips and the external environment in their study, including land use, socio-demographics, road design, transportation facilities, metro station characteristics, and DBS operator characteristics, which is of great relevance to our subsequent study. However, since the existing research data do not contain information on the built-up urban environment and individual attributes, very accurate modeling of regression and willingness models cannot be performed at this stage.

In future research, we will endeavor to obtain urban built environment data such as POI and conduct spatial regression models based on the known spatial heterogeneity. Secondly, we are already working on the design of a survey on travel intention of bike-sharing users, which will explore the degree of influence of weather environment, personal factors, cycling environment, subway environment, travel characteristics, environmental protection philosophy, and epidemic on people's willingness to use bike-sharing to connect, replace, and supplement the metro.

Data Availability

The dockless sharing bicycle data and metro automatic fare collection data used to support the findings of this study have not been made available because of the privacy policy.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

References

[1] C. S. Shui and W. Y. Szeto, "A review of bicycle-sharing service planning problems," *Transportation Research Part C: Emerging Technologies*, vol. 117, Article ID 102648, 2020.

[2] C. Xu, J. Ji, and P. Liu, "The station-free sharing bike demand forecasting with a deep learning approach and large-scale datasets," *Transportation Research Part C: Emerging Technologies*, vol. 95, pp. 47–60, 2018.

[3] M. Hatzopoulou, S. Weichenthal, H. Dugum et al., "The impact of traffic volume, composition, and road geometry on personal air pollution exposures among cyclists in Montreal, Canada," *Journal of Exposure Science and Environmental Epidemiology*, vol. 23, no. 1, pp. 46–51, 2013.

[4] Y. Lv, D. Zhi, H. Sun, and G. Qi, "Mobility Pattern Recognition Based Prediction for the Subway Station Related Bike-Sharing Trips," *Transportation Research Part C: Emerging Technologies*, vol. 133, Article ID 103404, 2021.

[5] Q. Yu, W. Li, D. Yang, and Y. Xie, "Policy zoning for efficient land utilization based on spatio-temporal integration between the bicycle-sharing service and the metro transit," *Sustainability*, vol. 13, no. 1, p. 141, 2020.

[6] 任逸帆 and 李开国, "共享单车对轨道接驳交通的影响分析. 交通与港航," 2018.

[7] J. Bachand-Marleau, B. H. Lee, and A. M. El-Geneidy, "Better understanding of factors influencing likelihood of using shared bicycle systems and frequency of use," *Transportation Research Record*, vol. 2314, no. 1, pp. 66–71, 2012.

[8] D. Zhuang, J. G. Jin, Y. Shen, and W. Jiang, "Understanding the bike sharing travel demand and cycle lane network: The case of Shanghai," *International journal of sustainable transportation*, vol. 15, no. 2, pp. 111–123, 2021.

[9] J. Song, L Zhang, L. Zhang, Z. Qin, and M. A. Ramli, "A spatiotemporal dynamic analyses approach for dockless bike-share system," *Computers, Environment and Urban Systems*, vol. 85, p. 101566, 2021.

[10] Y. Du, F. Deng, and F. Liao, "A model framework for discovering the spatio-temporal usage patterns of public free-floating bike-sharing system," *Transportation Research Part C: Emerging Technologies*, vol. 103, no. JUN, pp. 39–55, 2019.

[11] J. Bao, C. Xu, P. Liu, and W. Wang, "Exploring bikesharing travel patterns and trip purposes using smart card data and online point of interests," *Networks and Spatial Economics*, vol. 17, no. 4, pp. 1231–1253, 2017.

[12] Y. Zhang, T. Thomas, M. J. G. Brussel, and M. F. A. M. Van Maarseveen, "The characteristics of bike-sharing usage: case study in zhongshan, China," *International Journal of Transport Development and Integration*, vol. 1, no. 2, pp. 255–265, 2017.

[13] Y. Zhang, D. Lin, and X. C. Liu, "Biking islands in cities: an analysis combining bike trajectory and percolation theory," *Journal of Transport Geography*, vol. 80, p. 102497, 2019.

[14] R. B. Noland, M. J. Smart, and Z. Guo, "Bikesharing trip patterns in New York City: associations with land use, subways, and bicycle lanes," *International journal of sustainable transportation*, vol. 13, no. 9, pp. 664–674, 2019.

[15] K. Schimohr and J. Scheiner, "Spatial and temporal analysis of bike-sharing use in Cologne taking into account a public transit disruption," *Journal of Transport Geography*, vol. 92, no. 1, p. 103017, 2021.

[16] J. Mattson and R. Godavarthy, "Bike share in fargo, north Dakota: keys to success and factors affecting ridership," *Sustainable Cities and Society*, vol. 34, pp. 174–182, 2017.

[17] A. A. Campbell, C. R. Cherry, M. S. Ryerson, and X. Yang, "Factors Influencing the Choice of Shared Bicycles and Shared Electric Bikes in Beijing," *Transportation research, Part C. Emerging technologies*, vol. 67, pp. 399–414, 2016.

[18] K. Kim, "Investigation on the effects of weather and calendar events on bike-sharing according to the trip patterns of bike rentals of stations," *Journal of Transport Geography*, vol. 66, no. jan, pp. 309–320, 2018.

[19] W. L. Shang, J. Chen, H. Bi, Y. Sui, Y. Chen, and H. Yu, "Impacts of COVID-19 pandemic on user behaviors and environmental benefits of bike sharing: a big-data analysis," *Applied Energy*, vol. 285, Article ID 116429, 2020.

[20] S. Hu and C. Z. L. Xiong, "Examining spatiotemporal changing patterns of bike-sharing usage during COVID-19 pandemic," *Journal of Transport Geography*, vol. 91, no. 11, Article ID 102997, 2021.

[21] X. Chai, X. Guo, J. Xiao, and J. Jiang, "Analysis of Spatial-Temporal Behavior Pattern of the Share Bike Usage during COVID-19 Pandemic in Beijing," arXiv e-prints, 2020, https://arxiv.org/abs/2004.12340.

[22] D. Fuller, L. Gauvin, P. Morency, Y. Kestens, and L. Drouin, "The impact of implementing a public bicycle share program on the likelihood of collisions and near misses in Montreal, Canada," *Preventive Medicine*, vol. 57, no. 6, pp. 920–924, 2013.

[23] Y. Zhang and Y. Zhang, "Associations between public transit usage and bikesharing behaviors in the United States," *Sustainability*, vol. 10, no. 6, p. 1868, 2018.

[24] W. Zhu, Y. Pang, D. Wang, and H. Timmermans, "Travel behavior change after the introduction of public bicycle systems: case study in minhang district, Shanghai," in *Proceedings of the 92nd Annual Meeting Of the Transportation Research Board*, Washington, D.C, January 2013.

[25] E. W. Martin and S. A. Shaheen, "Evaluating public transit modal shift dynamics in response to bikesharing: a tale of two U.S. cities," *Journal of Transport Geography*, vol. 41, no. Dec, pp. 315–324, 2014.

[26] E. Fishman, S. Washington, and N. Haworth, "Bike share's impact on car use: evidence from the United States, Great Britain, and Australia," *Transportation Research Part D: Transport and Environment*, vol. 31, no. 2, pp. 13–20, 2014.

[27] D. Fuller, L. Gauvin, Y. Kestens, and P. L. Morency, "The potential modal shift and health benefits of implementing a public bicycle share program in Montreal, Canada," *International Journal of Behavioral Nutrition and Physical Activity*, vol. 10, no. 1, pp. 66–6, 2013.

[28] K. B. Campbell and C. Brakewood, "Sharing riders: how bikesharing impacts bus ridership in New York City," *Transportation Research, Part A. Policy and Practice*, vol. 100, pp. 264–228, 2017.

[29] H. Kong, S. T. Jin, and D. Z. Sui, "Deciphering the relationship between bikesharing and public transit: modal substitution, integration, and complementation," *Transportation Research Part D: Transport and Environment*, vol. 85, Article ID 102392, 2020.

[30] L. Böcker, E. Anderson, T. P. Uteng, and T. Throndsen, "Bike sharing use in conjunction to public transport: exploring spatiotemporal, age and gender dimensions in Oslo, Norway," *Transportation Research Part A: Policy and Practice*, vol. 138, no. 1, pp. 389–401, 2020.

[31] Q. Yu, W. Li, and D. Yang, "Policy zoning for efficient land utilization based on spatio-temporal integration between the bicycle-sharing service and the metro transit," *Sustainability*, vol. 13, no. 1, p. 141, 2020.

[32] Q. Yan, K. Gao, L. Sun, and M. Shao, "Spatio-temporal usage patterns of dockless bike-sharing service linking to a metro station: a case study in Shanghai, China," *Sustainability*, vol. 12, no. 3, p. 851, 2020.

[33] M. Adnan, S. Altaf, T. Bellemans, A. U. H. Yasar, and E. M. Shakshuki, "Last-mile travel and bicycle sharing system in small/medium sized cities: user's preferences investigation using hybrid choice model," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, no. 12, pp. 4721–4731, 2018.

[34] A. Sh, S. Hu, M. Chen, Y. Jiang, W. Sun, and C. Xiong, "Examining Factors Associated with Bike-And-Ride (BnR) Activities Around Metro Stations in Large-Scale Dockless Bikesharing Systems," *Journal of Transport Geography*, vol. 98, Article ID 103271, 2021.

[35] P. Jiménez, M. Nogal, B. Caulfield, and F. Pilla, "Perceptually important points of mobility patterns to characterise bike sharing systems: the Dublin case," *Journal of Transport Geography*, vol. 54, pp. 228–239, 2016.

[36] J. Zhao, J. Wang, and W. Deng, "Exploring bikesharing travel time and trip chain by gender and day of the week," *Transportation Research Part C: Emerging Technologies*, vol. 58, pp. 251–264, 2015.

[37] 李配配 and 崔珩, "公共自行车与轨道交通的接驳与换乘研究. 交通科技," no. 1, p. 4, 2013.

[38] T. Ma and G.-J. Knaap, "Estimating the impacts of capital bikeshare on metrorail ridership in the Washington metropolitan area," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2673, no. 7, pp. 371–379, 2019.

[39] Q. Yu, H. Zhang, W. Li, X. Song, D. Yang, and R. Shibasaki, "Mobile phone GPS data in urban customized bus: dynamic line design and emission reduction potentials analysis," *Journal of Cleaner Production*, vol. 272, p. 122471, 2020.

[40] Y. Qing and Y. Jian, "TransBigData: A Python Package Developed for Transportation Spatio-Temporal Big Data Processing, Analysis and Visualization," *Journal of Open Source Software*, vol. 7, no. 71, p. 4021, 2022.

[41] X. Ma, Y. Ji, Y. Jin, J. Wang, and M. He, "Modeling the factors influencing the activity spaces of bikeshare around metro stations: a spatial regression model," *Sustainability*, vol. 10, no. 11, p. 3949, 2018.

[42] Y. Ji, X. Ma, M. Yang, Y. Jin, and L. Gao, "Exploring spatially varying influences on metro-bikeshare transfer: a geographically weighted Poisson regression approach," *Sustainability*, vol. 10, no. 5, p. 1526, 2018.

[43] S. Hu, M. Chen, Y. Jiang, W. Sun, and C. Xiong, "Examining factors associated with bike-and-ride (BnR) activities around metro stations in large-scale dockless bikesharing systems - ScienceDirect," *Journal of Transport Geography*, vol. 98, p. 103271, 2022.

[44] Z. Wang and L. Y. Z. Cheng, "Spatiotemporal characteristics of bike-sharing usage around rail transit stations: evidence from beijing, China," *Sustainability*, vol. 12, no. 4, p. 1299, 2020.

[45] Y. Guo, L. Yang, Y. Lu, and R. Zhao, "Dockless bike-sharing as a feeder mode of metro commute? The role of the feeder-related built environment: Analytical framework and empirical evidence," *Sustainable Cities and Society*, vol. 65, p. 102594, 2020.

[46] W. Li, S. Chen, J. Dong, and J. Wu, "Exploring the spatial variations of transfer distances between dockless bike-sharing systems and metros," *Journal of Transport Geography*, vol. 92, p. 103032, 2021.

[47] D. Zhao, W. Wang, G. P. Ong, and Y. Ji, "An association rule based method to integrate metro-public bicycle smart card data for trip chain analysis," *Journal of Advanced Transportation*, vol. 2018, pp. 1–11, Article ID 4047682, 2018.

[48] Y. E. Hawas, M. N. Hassan, and A. Abulibdeh, "A multi-criteria approach of assessing public transport accessibility at a strategic level," *Journal of Transport Geography*, vol. 57, pp. 19–34, 2016.

[49] C. Wu and A. T. Murray, "Optimizing public transit quality and system access: the multiple-route, maximal covering/shortest-path problem," *Environment and Planning B: Planning and Design*, vol. 32, no. 2, pp. 163–178, 2005.

[50] S. T. Jin, H. Kong, and D. Z. Sui, "Uber, Public Transit, and Urban Transportation Equity: A Case Study in New York City," *Professional Geographer*, vol. 71, no. 2, pp. 315–330, 2019.

[51] 李孟冬, "步行可达性与地铁车站服务范围的研究," 生态文明视角下的城乡规划——*2008*中国城市规划年会论文集, 2008.