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Understanding the Competition and Cooperation between Dockless Bike-Sharing and Metro Systems in View of Mobility

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Abstract: The advent of dockless bike-sharing (DBS) represents an effective solution to enhance public transportation usage. However, despite growing interest in integrating DBS with metro systems, comprehensive studies on their competitive and cooperative relationships remain limited. This study aims to analyze the spatial, temporal, and mobility characteristics of metro-related DBS to explore integration opportunities. Initially, three modes of interaction between DBS and metros are identified: strong competition, weak competition, and feeder relationships. Subsequently, based on these relationships, the analysis focuses on distance, spatio-temporal patterns, and the scope of DBS activities. Results from Beijing indicate that metro-associated DBS primarily serves as "last-mile" solutions without significant short-range competition with metro systems. Strongly competitive relationships, on the other hand, are interaction patterns due to the dense overlay of metro stations and inconvenient transfer facilities and are mainly used for non-commuting purposes. Furthermore, weakly competing and feeder DBS systems exhibit similar commuting patterns, highlighting bicycling as a viable alternative to walking within metro catchment areas and that metro catchment areas should be adapted to bicycling. Mobility communities, identified as tightly integrated cycling hubs, are proposed as strategic dispatch zones to manage peak demands and reduce operational strain on DBS fleets. These findings deepen our understanding of DBS and metro system interactions, offering insights to optimize public transport operations and enhance urban mobility solutions.

Keywords: community-detection; DBS–metro integration; interaction relationship; spatial–temporal characteristics; mobility

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1. Introduction

Faced with global urban transportation and environmental challenges, there is a prevailing trend toward continual exploration and development of diverse green and sustainable transportation modes. With the rapid advancement of Internet technology, dockless bike-sharing, introduced by DBS companies, made its debut in China in 2016 [1]. Unlike traditional DBS systems with docking stations, DBS enables users to rent and return bikes from any location in the city, a feature that has garnered widespread acceptance among both governmental authorities and residents [2]. Companies are permitted by the government to invest significantly in DBS to accomplish two primary objectives. First, to supplant short-distance, high-emission transport. Second, to integrate DBS into the public transport network, thereby bridging the "last-mile" travel gap and promoting the utilization of public transport modes. In Guangzhou, China, 63% of DBS trips are linked to urban transportation stations [3]. Analogous to other emerging transportation modes, the advent and popularity of DBS have reshaped urban mobility patterns through interactions with various transportation modes. However, the impact of shared travel on urban travel patterns is intricate. While it may replace high-emission intensity modes of transport, it may also supplant low-emission intensity modes of transport, and it may even engender some rebound effects. In essence, DBS not only presents an alternative to car travel but

also intensifies competition with public transport, particularly for short trips. Although the emergence of DBS has precipitated a paradigm shift, fewer than 20% of trips have transitioned from cars to DBS (e.g., Barcelona, Shanghai, Washington DC), with even fewer than 10% in cities like London and Lyon [4]. This means that DBS may not be an adjunct to public transportation. In China, nearly half of DBS activities occur in proximity to metro stations, with 51% of bicycles parked within 500 m of metro station areas [5]. Therefore, further exploration of the dynamics of competition and cooperation between DBS systems and public transport, especially concerning interactions with the metro, is imperative.

Enhancing the integration of DBS with public transportation is a pivotal aspect of DBS research [6]. Numerous studies have concentrated on promoting the integration of DBS with metro systems [7]. The correlation between DBS and metro passenger flow has been studied. Zhang et al. [8] investigated the correlation between metro ridership and DBS usage, revealing a significant positive correlation between metro utilization and DBS usage. In addition, the characteristics of transit trips in DBS–metro are also studied. Liu et al. [9] examined last-mile connections to urban rail transit in Beijing, China, utilizing DBS and buses. The specific integration range between bike-sharing and metros ranges from 0.5 to 3 km. In Zhao's [10] study, first-mile trips during the morning rush hour exhibit a spatial pattern identical to that of last-mile trips during the evening rush hour and are shorter than other DBS trips that complement metro travel. In terms of spatial and temporal characteristics, China's experience indicates that bike-sharing in downtown areas act as a feeder mode for the metro, exhibiting a substitution effect for buses [11]. Suburban commuters primarily use motorized transport, such as ride-hailing and taxis, to connect to metro stations. Conversely, in European cities like Oslo, bike-sharing complements public transport, bridging gaps in areas without public transit access [12]. In some North American cities, residents on the city's outskirts tend to integrate bike-share travel with bus and subway trips [13]. Thus, in Western countries, where metro stations are more dispersed, bike-sharing is more likely used as a feeder, especially in suburban areas. Furthermore, various factors influencing integration are meticulously examined, encompassing psychological factors, built environment, and metro station attributes. Puello et al. [14] scrutinized the relationship between three potential variables (perception of connectivity, attitude towards station environment, and perceived quality of bicycle facilities) and the metro–DBS model, revealing that all variables positively contribute to integration between the two. In less densely populated suburbs, DBS exhibits a stronger association with metros [13]. Zhao et al. [15] determined that residential areas serve as the primary source of demand for DBS, while metro stations emerge as the most appealing destinations for concluding DBS trips. In addition, areas with more mixed land use have resulted in more bicycle trips to and from metro stations in different cities around the world, including Melbourne [16] and Toronto [17]. Nair et al. [18] discovered that within a specified area (300–800 m) surrounding a metro station, the presence of bicycle-related infrastructure, such as bicycle lanes, exhibited a positive correlation with the number of metro passengers. If public transportation and DBS can synergize and establish a partnership instead of competition, the service level of the integrated transportation system will witness significant enhancement [19]. Infrastructure and economic policy measures, such as installing parking stations near metro entrances, have been enacted to bolster DBS integration with the metro. However, to formulate a reasonable coordinated development policy, it is imperative to elucidate the relationship between the two and understand the characteristics of DBS usage.

Therefore, it is imperative to understand the usage characteristics of DBS near metro stations and to elucidate the competition and cooperation relationship between the metro and DBS. This understanding will facilitate the accurate positioning of each transportation mode and promote mutually beneficial cooperation between them, thereby fostering the advancement of urban mobility. The objectives of this paper are twofold: (1) to analyze the competitive and cooperative dynamics between metro systems and bike-sharing; and (2) to understand the spatio-temporal characteristics and mobility patterns of interactions

between bike-sharing and metros, including origins, destinations, and activity ranges. This study primarily utilizes the flow of bike-sharing near metro stations to explore the usage characteristics of the DBS system. Specifically, we delineate the competition and cooperation relationship between bike-sharing and the metro into three types: strong competition, weak competition, and feeder. Subsequently, by leveraging DBS order data and the spatial distance between the metro and DBS, we explore travel distance as well as temporal and spatial characteristics. We then employ a community partitioning algorithm to understand the mobility of bike-sharing in the three metro–DBS modes, analyzing both weekdays and weekends to refine the results. This study aims to address the following three questions: (1) What are the characteristics of the three modes in terms of distance and time of travel? (2) Do the spatial characteristics of the three models differ under different time conditions (weekdays and weekends)? (3) What is the liquidity of the three models under different time conditions? By analyzing the usage pattern of the DBS system to the metro, the results of this study can provide support for understanding the rational planning and scheduling of the DBS system and its integration with the metro.

The subsequent sections are structured as follows. The next section will introduce the data of the study area and DBS. Subsequently, this paper delineates the relationship between DBS and the metro and outlines the analysis method for DBS mobility. The subsequent section analyzes the spatio-temporal and mobility characteristics of the three modes of DBS. Finally, a discussion and conclusions are provided.

2. Data

2.1. Study Area

Beijing, one of China's mega-cities and the political and cultural center of the country, spans an area of 16,400 square kilometers and hosts a population of 21,843,000 people. Our study focuses on the area within the sixth ring road, encompassing over 70% of the city's built-up area and more than 80% of public transport trips [20]. This area is serviced by a comprehensive metro network, boasting 27 operational lines as of 2022, covering 836 km and accommodating an average daily passenger flow of 9,434,000 passengers. All rail stations within Beijing are included in our study area. Additionally, the total number of bike-sharing rides in the city reached 968 million, with bike-sharing widely available throughout urban areas, serving a significant portion of the population. Given the extensive infrastructure and high urban travel demand, this location provides an excellent opportunity to examine the potential relationship between metros and DBS (Figure 1).

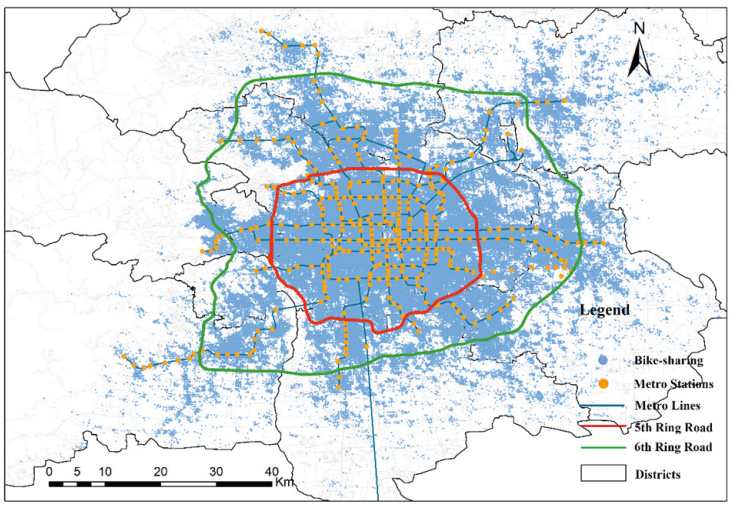


Figure 1. Research area.

2.2. DBS Dataset

This study used data from the public dataset of the Algorithm Challenge held by Mobike, providing DBS order data in Beijing from 10 May to 24 May 2017, comprising 3,214,096 records. In 2017, Mobike accounted for 57% of the bike-sharing market. Each data entry includes trip details such as order ID, user ID, bike ID, start time, start position, and end position. Geohash is a method for encoding addresses, dividing geographic areas into grids, and encoding latitude and longitude into broader areas. The geohashed_start_loc and geohashed_end_loc in Table 1 denote the start and end grids of bike-sharing, respectively. When bike-sharing trips fall within the same geohash grid, their start and end points are considered the same, making specific locations indistinguishable within that grid. The length of the string corresponds to the precision of the represented area. In the dataset, the encoding comprises 7 bits, offering a resolution of approximately 110 m × 150 m.

Table 1. Transportation infrastructure indicators.

Order ID	User ID	Bike ID	Bike Type	Start Time	geohashed_start_loc	geohashed_end_loc
4657992	1061133	465394	1	10 May 2017 20:16	wx4dr59	wx4dquz
4548579	489720	456688	1	12 May 2017 20:18	wx4d5r5	wx4d5r4
5163705	917620	509044	1	13 May 2017 06:06	wx4gd2e	wx4g6pw
19818	583391	3190	1	15 May 2017 21:23	wx4fhkk	wx4fh7q
495333	185893	67441	1	16 May 2017 14:12	wx4emgw	wx4emgk
289754	426024	40489	1	16 May 2017 11:27	wx4dy2p	wx4dwxv

Weather serves as a significant variable influencing bike-sharing trips. Saneinejad et al. [21] explored the impact of weather variables, including wind, precipitation, and temperature, on bicycling. Among these, temperature was the sole factor positively correlated with cycling activity. Consequently, bike-sharing rentals exhibit a seasonal pattern, with reduced usage in winter and peak usage in summer. However, seasonal weather variations have a limited effect on the total number of shared bike trips, as weather is more likely to influence occasional cyclists than regular cyclists [22,23]. To mitigate the effects of weather in our study, we selected a representative dataset from the week of May. Weekly usage remains relatively consistent between May and October, excluding the peak summer months [24]. This allows us to minimize seasonal effects and ensure the representativeness of our data. Furthermore, we aimed to exclude the potential impediment of adverse weather conditions, such as rain and snow, on bike-sharing trips. The dataset comprises DBS data from the week spanning 10 to 16 May 2017, encompassing weekdays (10–12 May, Wednesday to Friday; 15–16 May, Monday to Tuesday) and weekends (13–14 May). During the study period, weather conditions remained consistently cloudy to sunny, with temperatures ranging from 27 °C to 32 °C, which are favorable for cycling. It is crucial to acknowledge that the travel patterns of each day of the week may be subject to bias, and it is challenging to select a single day that adequately captures the full spectrum of travel characteristics. Therefore, to mitigate the influence of the chosen day, we opted to include a complete week in our analysis. By encompassing the entire week, including midweek days, we aim to more accurately represent weekday and weekend travel patterns.

To ensure data quality, the analyses are based on DBS data after data cleaning. During the data preprocessing stage, we used the geohash package in Python3.8 to convert encoding into latitude and longitude. Furthermore, duplicate entries and trips shorter than 150 m or longer than 5 km were excluded. Consequently, we obtained 31,547,716 valid trip records for DBS. Among these records, the average trip distance is 803 m, with trips spanning 0–2 km accounting for 96% (Figure 2).

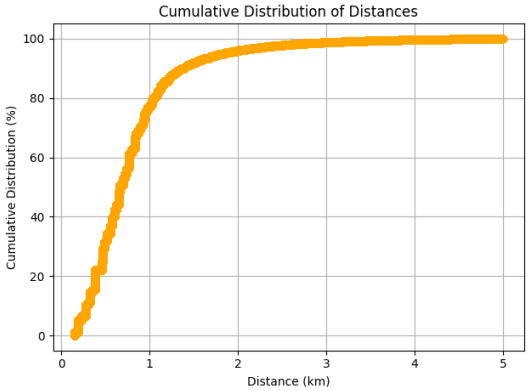


Figure 2. Cumulative distribution of distances.

3. Methodology

3.1. The Relationship between the Metro and DBS

Public transport is a fundamental part of urban transport, in which the metro system plays a pivotal role. A great deal of work has been carried out in China to increase the percentage of public transport, including the expansion of lines and the introduction of intermodal fares. Since the emergence of DBS in China in 2016, the flexibility of urban transport management has increased. The feeder mode of public transport is a key function of bike-sharing. It effectively solves the last-mile (or first-mile) problem by enhancing connectivity to metro stations. Improvements in the quality and efficiency of feeder systems enhance the attractiveness of the metro network. In addition, DBS and public transport can replace short trips of 1 to 3 km [25]. A survey conducted in Shanghai in 2016 showed that 19.7% of DBS users chose bikes over buses and 7.8% chose bikes over the metro [26], suggesting that there is an intricate interplay between DBS and the metro system.

In this study, the interaction between bike-sharing and the metro is categorized into three types: strong competition, weak competition, and feeder relationships. First, defining the metro's catchment, within which DBS–metro interactions occur, is crucial. A circular area (access zone) centered on each metro station designates this catchment. Establishing an appropriate radius for this circular area is a challenge. A buffer that is too small may ignore bicycle trips, while one that is too large may include activity outside the underground system. For example, residents near metro stations often use DBS for dining and shopping outings. Ji et al. [27] found that 90% of transfer trips occur within 300 m, with a strict range of 100 m for DBS connections to the metro [28,29]. Thus, the 100–300 m range around stations is recognized as a valid connection zone. To accurately capture metro–DBS trips, we aimed to maintain this boundary as close to 100 m as possible. Given the data's resolution (approximately 110 m $\times$ 150 m), we opted for a 150 m circular buffer around each metro station in line with Li et al.'s [30] study. This buffer range represents the minimum threshold for identifying connected trips. DBS origin–destination (OD) pairs within 150 m of a station are categorized as showing strong competitive relationships. According to the guidelines for Transit-Oriented Development (TOD) in China's Urban Rail Transit Planning and Design Guidelines from the Ministry of Housing and Urban-Rural Development, an 800 m threshold is set for organizing urban spaces and activities around metro stations [31]. This distance, equivalent to a 15 min walk, is commonly considered the maximum comfortable walking distance [32,33]. Residents within 800 m of a metro station are four times more likely to use public transportation than those farther away [34]. Therefore, this study defines the metro station's catchment area as 800 m. We argue that bike-sharing trips indicate weak competition when one end is within 150 m of a station and the other is between 150 m and 800 m, as both ends fall within the metro station catchment area. Additionally, a bike-sharing trip is considered a feeder if one end is within 150 m of a station and the other is beyond 800 m. These three relationship types are illustrated in Figure 3.

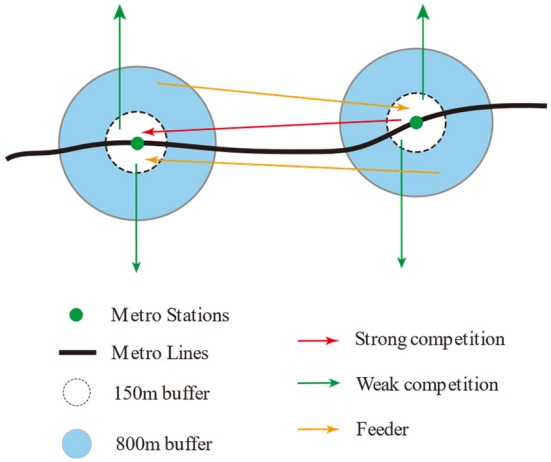


Figure 3. Competition and partnership between metro and DBS.

3.2. Mobility Community Detection of DBS

Community detection plays a crucial role in extracting valuable insights from networks. One pivotal application is the identification of communities, groups of nodes more closely connected than others in the network. These communities are prevalent in various complex systems, including sociology, biology, and transportation [35]. Detecting communities aids in understanding the relationship between network structure and system behavior. This study applies community detection to describe and analyze interaction patterns in metro–DBS systems. First, identifying densely interconnected segments within the bike-sharing mobility network reveals the extent of bike mobility. Second, understanding the spatial relationships between clusters of bike-sharing communities and clusters of metro stations helps determine which stations are interconnected through bike-sharing.

3.2.1. Network Construction

Community structure is a prominent feature in various large networks, such as social networks with multiple communities and urban transport networks. In this study, we utilized directed and weighted networks to model the bike-sharing network G (V, E, W). The node set V consists of geohash codes representing the start and end points of DBS, where each geohash code corresponds to a node. The edge set E represents connections between nodes, with an edge established when a bike-sharing trip occurs between different nodes. The edges E_{ij} are inherently directed, indicating the direction of travel. In the absence of trips between two points, the weight is set to 0. Additionally, by considering the weight of each edge, we quantify the strength of the connection, reflecting the flow between nodes. Analyzing the network structure facilitates understanding of mobility patterns across various modes of DBS.

3.2.2. Community Detection

In a bike-sharing network, certain nodes exhibit denser connections among themselves, while others are sparsely connected. The densely connected nodes can be identified as a community, with relatively sparse connections between communities, forming the overall community structure. Various methods are available for community detection, and we chose the fast-unfolding algorithm for detecting communities in bike-sharing networks [35]. The process of the fast-unfolding algorithm unfolds as follows:

Step 1: Initially, consider each node in the network as an independent community.

Step 2: Sequentially attempt to assign node i to the community of each of its neighboring nodes. Calculate the change in modularity (Δ) for each assignment. Record the neighboring node with the largest Δ. If $\Delta > 0$, assign node iii to the community of the neighboring node with the largest Δ; otherwise, leave it unchanged.

Step 3: Repeat Step 2 until the community assignments of all nodes stabilize and no further changes occur.

Step 4: Transform the edge weights of nodes into the weights of the new nodes.

Evaluating the quality of partitioning is a crucial step in community detection. Modularity is employed to gauge the effectiveness of partitioning results, formalized as shown in Equation (1). The greater the modularity, the better the community partitioning results. Typically, when the modularity value ranges from 0.3 to 0.7, the partitioning is deemed highly effective. The principle behind modularity is that dividing closely connected nodes into the same community increases the modularity value. The modularity Q-value is defined as follows:

$$Q = Q_1 - Q_2 = \frac{1}{2m}\sum_{i,j}[A_{ij} - \frac{k_i k_j}{2m}]\delta(c_i, c_j) \quad (1)$$

$$Q_1 = \frac{1}{2m}\sum_{i,j}^{n}(A_{ij}\delta(c_i, c_j)\sum_{c}\delta(c_i, c)) = \frac{1}{2m}\sum_{c}(\sum_{(i,j):ci=cj=c} A_{ij}) \quad (2)$$

$$Q_2 = \frac{1}{2m}\sum_{i,j}^{n}(\frac{k_i k_j}{2m}\delta(c_i, c_j)\sum_{c}\delta(c_i, c)) = \frac{1}{2m}\sum_{c}(\sum_{(i,j):ci=cj=c} \frac{k_i k_j}{2m}) \quad (3)$$

where Q_1 represents the Q-value of the overall network topology, Q_2 represents the Q-value of the partitioned stochastic model, and A_{ij} denotes the weight between i and j. $k_i = \sum_j A_{ij}$ is the sum of the weights of all nodes, c_i is the community to which i belongs, $m = \frac{1}{2}\sum_{ij} A_{ij}$ denotes the sum of the weights of all edges, and $\delta(c_i, c_j)$ is 1 when c_i and c_j arguments are equal; otherwise, $\delta(c_i, c_j)$ is 0.

4. Results

4.1. Travel Distance Characteristics of DBS

To gain deeper insight into trip distance characteristics, probability density distributions were used to describe the distance distributions of the three modes (shown in Figure 4). Distance calculation involved converting geohash codes into latitude and longitude using Python's geohash library. All three modes of DBS exhibit similar probability density distributions on both weekdays and weekends. The distance distribution for feeder DBS on weekdays and weekends centers around 0.8 km, while for weak competition, it centers around 0.9 km. These two modes show comparable distance distributions, suggesting similar travel purposes. In contrast, strong competition shows bimodal peaks at approximately 0.4 km and 1 km, potentially reflecting passengers' needs to travel longer distances for transfers despite being within the metro's catchment area. Considering factors such as travel time and comfort, passengers may choose to exit the station at a transfer point close to their destination and use DBS to complete their journey. The denser concentration of metro stations in the city center compared to the suburbs likely contributes to these two peaks. It is important to note that the trip distances reported in this section are slightly underestimated, as we calculate the straight-line distance between origin and destination points.

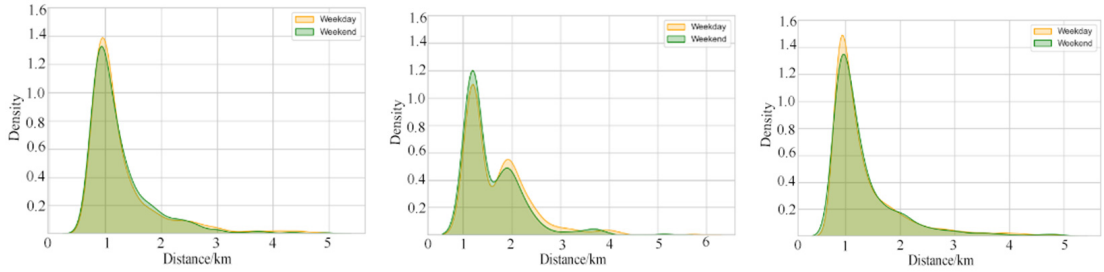


Figure 4. The probability density distribution of travel distance in the three modes on weekdays and weekends (from left to right, feeder, strong competition, weak competition).

4.2. Spatio-Temporal Patterns of DBS Travel

In this section, we begin by exploring the temporal characteristics of the three bike-sharing modes. Using the Python platform, we counted the number of bike-sharing trips per hour based on unlocking time. Figures 5 and 6 illustrate the total number of hourly trips over a week, categorized according to the three metro–DBS relationships outlined earlier. Generally, each mode shows similar temporal trends on both weekdays and weekends. Weekdays exhibit two distinct peaks (7:00–9:00 and 17:00–19:00), along with a noticeable midday peak (11:00–13:00), typically associated with short trips taken during lunch breaks [36]. These peaks are likely attributed to commuting. Over five consecutive workdays, there were noticeable patterns in bike-share usage. In the morning peak, Monday typically exhibited lower bicycle usage compared to other weekdays. This may be attributed to the diversification of commuting modes after weekend leisure activities, such as ride-hailing services and private cars. Tuesday, Wednesday, and Thursday showed a more consistent volume of trips, likely due to the regular "two points, one line" commuting pattern between home and work. In contrast, during the evening peak, Friday demonstrated a trend of decreased bicycle usage compared to the morning peak, approximately 8% lower than Wednesday and Thursday. This reduction can be explained by the complexity of Friday travel patterns, with weaker ties to the home. However, the total number of trips for strong competition relationships is the lowest, with a more evenly distributed pattern throughout the day. These bikes may be used for irregular trips such as shopping and leisure. On weekends, Saturdays and Sundays show similar patterns. Unlike weekdays, weekends lack a clear double peak, with the highest volume of travel occurring during the evening rush hour. This is rational as most individuals do not need to commute on weekends, and residents use DBS for daily activities such as shopping and leisure. These findings reaffirm that DBS associated with the metro is primarily utilized for commuting rather than leisure, a trend observed similarly in other large cities in China such as Shanghai and Shenzhen [37–39]. Similarly, in South Korea, leisure trips increase the use of DBS in the afternoon on weekends, while commuting trips on weekdays drive demand for DBS during peak hours. Particularly on weekends, demand for bikes in parks was twice as high as on weekdays [40].

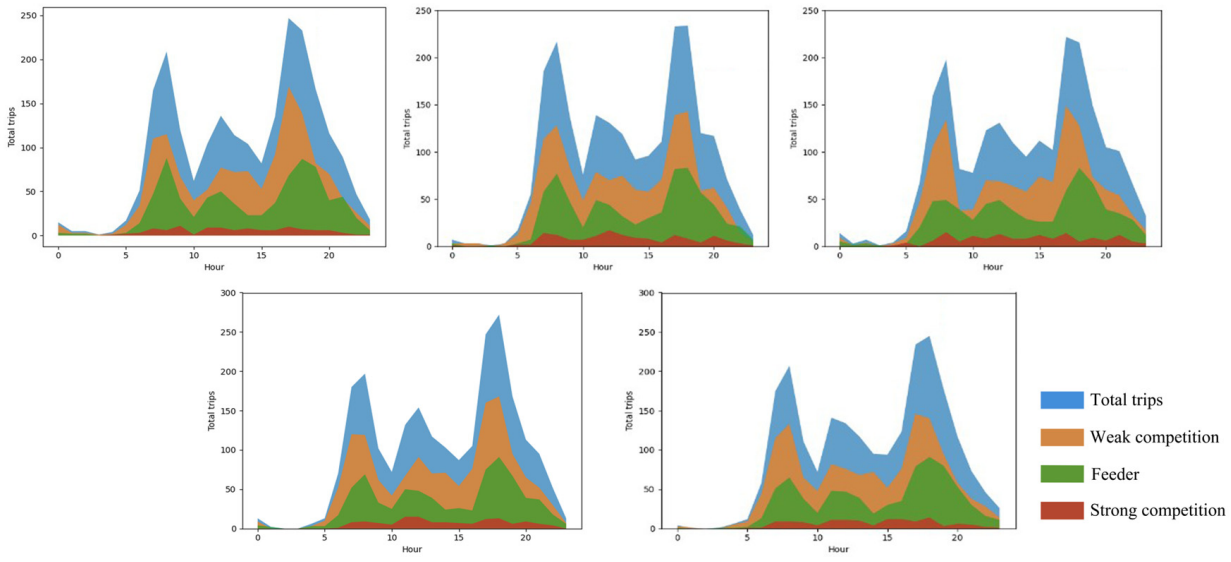


Figure 5. The time distribution of the travel volume of the three modes of bike-sharing on weekdays.

Subsequently, we analyze the spatial distribution of origins and destinations for the identified subset of DBS trips with metro connections. ArcGIS10.2 is used to map the spatial distribution of bicycle usage at start and end points. A radius of 800 m around each station is defined as the catchment area, within which bicycle usage is analyzed. Starting points of the bicycles are imported into ArcGIS, and end points are exported from the relevant

data tables for visualization of their spatial distribution. For feeder bikes whose termini fall outside the catchment area, kernel density estimation (KDE) is applied to identify hot spots. The primary formula for kernel density estimation is as follows:

$$f(s) = \sum_{i=1}^{n} \frac{1}{nh} k\left(\frac{S - c_i}{h}\right) \quad (4)$$

where $f(s)$ is the kernel density estimation function at spatial position S, h is the distance attenuation threshold (i.e., bandwidth), n is the number of factor points within a distance h from the evaluation point S, k represents the spatial weight function, and $S - c_i$ is the distance from the estimation point c_i.

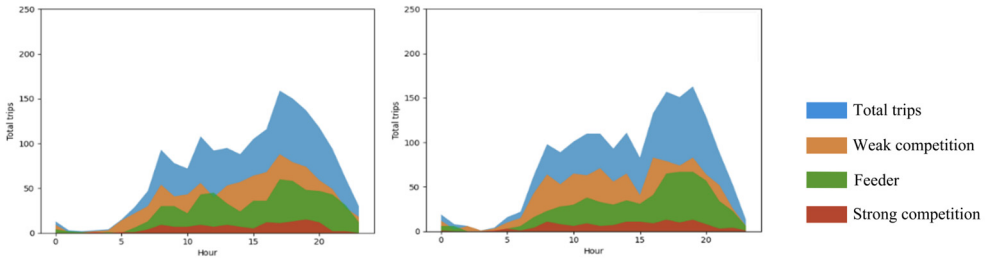


Figure 6. The time distribution of the travel volume of the three modes of bike-sharing on weekends.

The stations are categorized into weekdays and weekends to depict the spatial demand distribution for DBS trips across the three modes, illustrated in Figures 7–10. The spatial distribution of trips for the three modes on weekdays and weekends is visualized using the 800 m metro buffer as a unit. Green and red colors indicate lower and higher bicycle trip volumes, respectively. Overall, trip volumes for all three modes are notably lower on weekends compared to weekdays. As expected, DBS trip volumes decrease towards the periphery from metro stops. Trips are primarily concentrated at metro stops within the fifth ring road, characterized by dense residential and commercial areas. Fewer trips were observed between the fifth and sixth ring roads. Additionally, a few stations account for a larger share, typically located in city center areas or near key public transport hubs (e.g., CBD, Shougang Industrial Park).

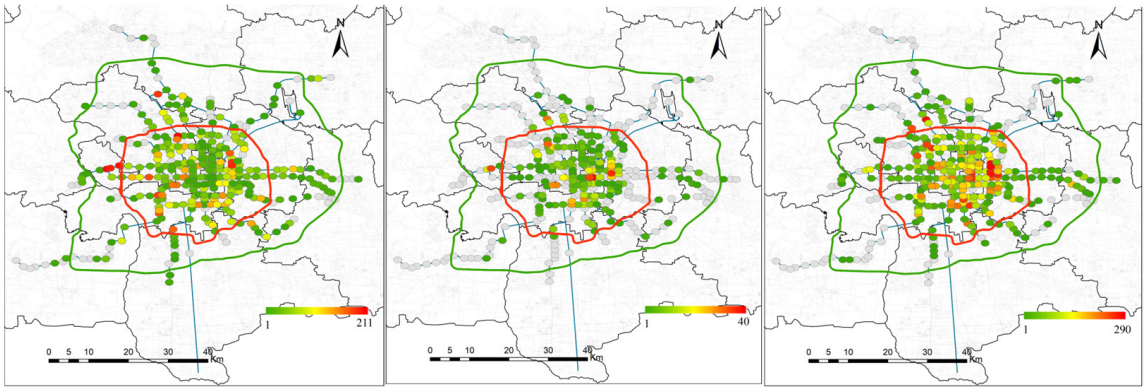


Figure 7. Weekday order starting points (from left to right, feeder, strong competition, weak competition).

We identified hot spots for feeder bikes, with Zhongguancun and Shougang Industrial Park standing out due to their high travel volumes. Prominent hot spots also include stations in the CBD, Shilibao, and Financial Street areas within the fourth ring road. It is notable that few shared bicycles operate outside the metro network due to sparse metro lines and long distances exceeding suitable cycling ranges. In such cases, travelers may opt for buses or online car services instead. Bikes involved in strong competition operate within 150 m of metro stations and are frequented over distances of 0.4 km to 1 km. This

aligns with expectations of intense competition between DBS and the metro, where metro stations drive economic activity in surrounding areas, featuring shopping centers and parks. Commuters often choose to exit at transfer stations near their destinations and use bike-sharing to complete their journeys, facilitated by the dense metro station network in central areas. Identifying starting points at transfer stations helps highlight stations lacking convenient transfer facilities. Weak competition bikes exhibit characteristics similar to feeder bikes, with hot spots concentrated in employment areas such as CBD, Shangdi, Zhongguancun, and Wangjing. These hot spots diminish on weekends, confirming their weekday commuting focus. This suggests that commercial facilities along metro lines play a crucial role in both commuting and non-commuting trips using feeder bikes. End points for weak competition bikes show consistency between weekdays and weekends, predominantly located in eastern metro stations. Notably, the CBD area sees significant DBS usage throughout the week, highlighting its role as a key business center for both commuting and non-commuting trips by residents.

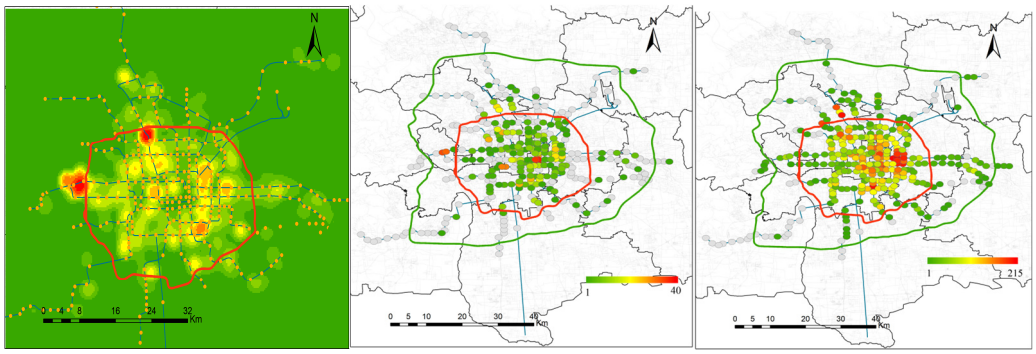


Figure 8. Weekday order end points (from left to right, feeder, strong competition, weak competition).

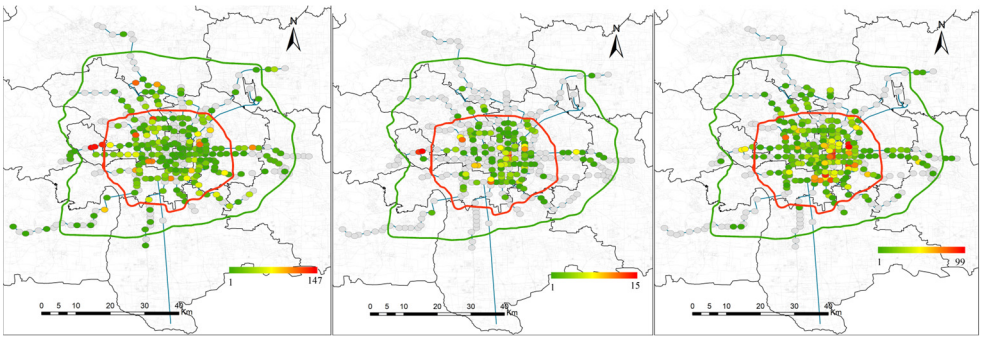


Figure 9. Weekend order starting points (from left to right, feeder, strong competition, weak competition).

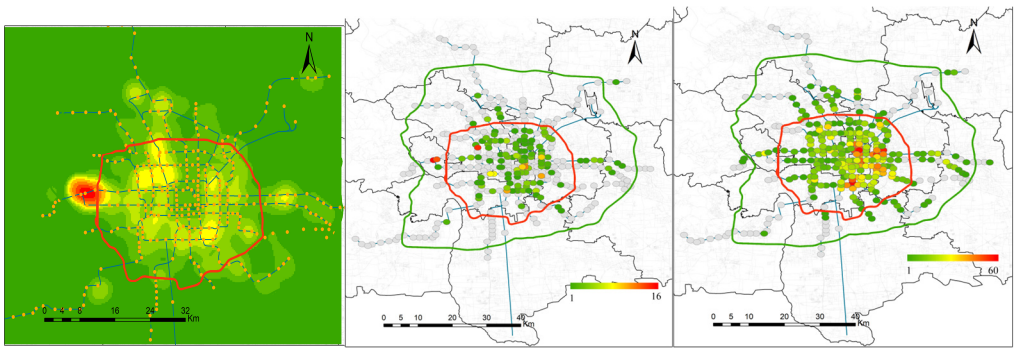


Figure 10. Weekend order end points (from left to right, feeder, strong competition, weak competition).

4.3. Mobility Community of DBS

Figures 11–13 illustrate the activity range of feeder, strong competition, and weak competition modes on weekdays, weekends, and over a full week. Different colors indicate different communities. The squares in the figure represent a geohash grid, which is 110 m × 150 m. In the feeder scenario, a distinct community structure was generally absent during weekends but became more apparent when analyzing the entire week as the statistical unit. This implies that the feeder's community structure primarily emerges during weekdays, underscoring the commuting nature of feeder bikes. Thus, aggregating feeder destinations offers a clearer perspective of the city's employment hubs. Additionally, in all three cases, the feeder mode exhibits a broader range of travel in areas with limited metro service coverage. Figure 12 reveals two types of communities: (1) Prominent employment areas such as Fengtai Science Park and Wangjing persist across both weekday and weekly community structures. (2) Stable patterns on weekdays, weekends, and the entire week are observed, exemplified by Shougang Industrial Park. To address the commuting efficiency of nearby residents in the second community type, the supply capacity of shuttle buses and online car-booking services could be considered. In the strong competition scenario, an evident community structure is lacking, with most bicycles shuttling between 2 and 3 metro stations. The community clusters within the fourth ring road, with scattered structures on the periphery. The dense distribution of metro stations and the presence of weak areas have contributed to the prevalence of highly competitive bicycles. This further underscores that competitive bicycles do not directly compete with metro travel but serve as auxiliary transportation in metro-deficient areas. In the weak competition scenario, the community structure resembled that of the feeder scenario, featuring a clear structure on weekdays and a scattered one on weekends. However, the weak competition bike community structure is more pronounced compared to that of the feeder community, with a concentration in denser metro areas. In Beijing, the presence of DBS within metro systems is essential, aiding in accessibility to areas that are not easily reachable directly by metro. In other large cities, such as Washington, D.C., TAZs with high levels of bike-sharing trips are similarly adjacent to metro lines [41].

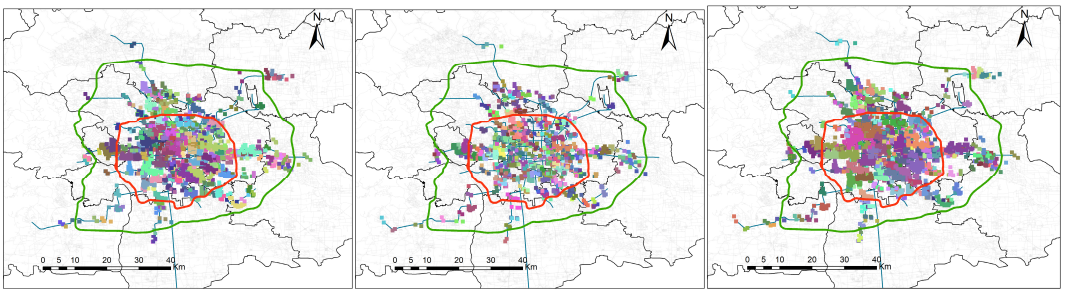


Figure 11. Mobile community with feeder bikes (left to right, weekdays, weekends, a week).

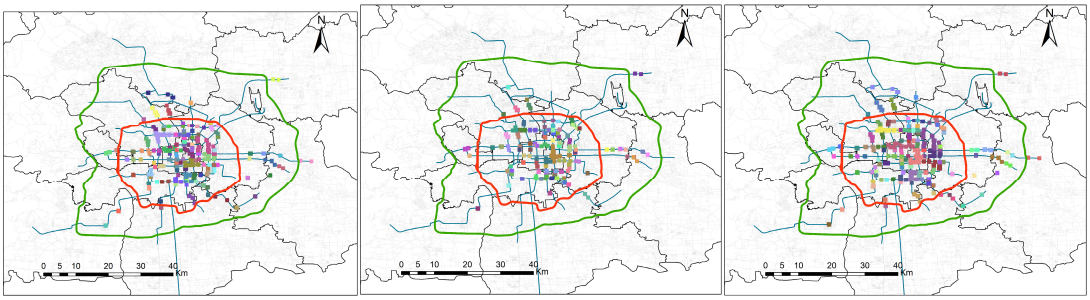


Figure 12. Mobile community with strong competition bikes (left to right, weekdays, weekends, a week).

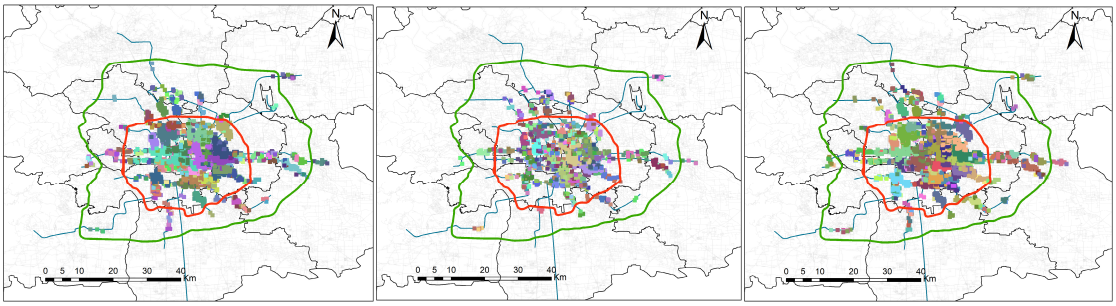


Figure 13. Mobile community with weak competition bikes (left to right, weekdays, weekends, a week).

5. Discussion

Drawing on the spatial correlation between bike-sharing and the metro, we categorize three types of metro–DBS relationships and examine the spatial, temporal, and travel attributes of each bike-sharing category. Statistical analyses indicate that in Beijing, bike-sharing integrated with the metro predominantly serves as a supplement to metro journeys. Additionally, we advocate for identifying bike-sharing communities to assess their mobility patterns and to delineate the extent of bike-sharing activities for further exploration of the interaction between bike-sharing and the metro.

The findings highlight that in Beijing, both feeder and weak competitive bike-sharing show two prominent peak periods with a minor peak at midday on weekdays. This pattern suggests that commuting is the primary reason for travel among users. To mitigate traffic congestion and shorten commute times, commuters often choose bike-sharing (DBS) over buses for short trips or as last-mile connections to urban rail systems. These observations align closely with previous research on DBS usage patterns [41–43]. Additionally, the 800 m catchment area is traditionally based on a comfortable walking distance, yet the patterns observed with feeder and weakly competitive bicycles indicate that cycling has emerged as a robust alternative to walking. This shift is driven by cycling's advantages in travel efficiency and physical exertion. Bike-sharing systems have effectively expanded the reach of metro stations, making the 800 m boundary less relevant. Therefore, there is a need for further analysis to redefine the transit-oriented development (TOD) area based on the travel range of bike-sharing associated with the metro. Additionally, it is essential to refine the design of cycling facilities and improve the environment around metro stations to enhance connectivity between rail systems and bike-sharing, thereby improving overall metro service coverage. Strong competitive bike-sharing shows an evenly distributed number of trips per hour, with consistent travel patterns observed on both weekdays and weekends. These bikes are frequently used for sporadic purposes like shopping and leisure. It is crucial to distinguish between commuting, utility-oriented travel, and leisure travel [44] to determine when, where, and which bicycles should be prioritized in advocating for the transition from high-emission travel to bike-sharing systems (DBS).

In the mobility analysis, feeder and weak competition DBS modes exhibit similar community structures on weekdays, reinforcing the findings that these modes primarily serve commuting purposes. DBS operators must strategically dispatch bikes to maintain balanced distribution across different locations, avoiding oversupply and shortages. Community boundaries offer viable management and scheduling parameters, as advocated by Wang [45]. It means that bikes within a community have a higher turnover rate, and when community boundaries are defined, bikes are not scheduled to adjacent areas. The maximum range of bicycle flow within a community allows enterprises to conduct localized scheduling, which helps save costs and reduce the strain on dispatching vehicles.

It is noteworthy that the majority of DBS trips occur within a 3 km radius, providing a competitive and viable alternative to buses for medium-distance trips (up to 3 km). This preference is intuitive, as cycling is typically constrained by physical endurance over longer distances. DBS usage peaks around distances of 0.4 km and 1 km. Shorter travel distances suggest that passengers often choose DBS to reach nearby metro stations or

transit hubs, factoring in considerations such as travel time and comfort. This observation is supported by Zhong et al. [46], who argue that areas surrounded by metro lines may pose challenges for metro passengers, potentially requiring multiple transfers or detours despite the relatively short distance between origin and destination points. Therefore, DBS plays a crucial role in facilitating these short trips.

6. Conclusions

Integrating dockless bike-sharing (DBS) with metro systems as an efficient and sustainable mode of travel contributes significantly to reducing car use and promoting the development of green and sustainable cities. Despite increasing interest in DBS and metro integration, few studies comprehensively explore their competitive and cooperative relationships to maximize integration potential. Therefore, this study aims to analyze DBS interactions with the metro using data from Beijing. The findings will enhance understanding of how DBS and metro systems interact, identifying areas where DBS competes or cooperates with the metro to optimize integration.

Key findings and recommendations from this study deserve emphasis. First, this study categorizes interactions between metro systems and dockless bike-sharing (DBS) into three modes: strong competition, weak competition, and feeder. In Beijing, there is minimal direct competition between DBS and the metro for short distances, as feeder and weak competition bikes predominantly serve the last kilometer. Strong competition arises due to dense metro station clusters and inconvenient transfer facilities, highlighting the essential role of DBS in extending metro coverage to areas not easily accessible. These insights are transferable to similar cities. Second, both weak competition and feeder bikes show distinct commuting characteristics, with weak competition bikes displaying stronger commuting patterns compared to feeder bikes. Identified mobile communities, where internal bike flows exceed those between communities, can be leveraged as effective dispatch zones to forecast and manage bike demand proactively. This approach helps alleviate bike shortages during peak periods and optimizes DBS integration with metros. Third, DBS in Beijing effectively complements metro services. To enhance this cooperation, urban planners and policymakers should prioritize improvements to the bicycle infrastructure. This includes installing signage, anti-skid measures, and optimizing parking facilities based on demand. Maintaining cycling infrastructure is crucial for ensuring safety and convenience, thereby promoting sustainable urban mobility.

While this study provides clarity on the interaction between DBS and the metro, it is essential to acknowledge its limitations. Firstly, the availability of data poses a constraint. The OD (origin–destination) data for DBS are defined by geohash coding, which confines locations to 110 m $\times$ 150 m grids. The positional offset introduced by the geohash data format, when compared to longitude and latitude, can potentially lead to inaccuracies in identifying DBS–metro trips. Specifically, bicycles within the same geohash grid are treated as having the same end point, obscuring features such as the actual distance traveled by DBS users. Additionally, depending on the geohash accuracy, the actual coordinates of bike-sharing tend to be biased towards the center of rectangular grids of varying sizes. This limitation can result in errors in identifying metro-related bike-sharing, potentially including either more or fewer bikes than would be expected. However, studies indicate that 90% of bike-sharing occurs within 300 m of metro stations, significantly more than the 150 m range we chose. Additionally, when identifying community structures, the community detection method uses grids as nodes, with many studies employing equal-sized meshes (e.g., 250 m $\times$ 250 m) [45]. Our data format offers higher resolution, minimizing the impact of these limitations. We can still try to obtain latitude and longitude data for a more detailed analysis. Alternatively, we can assume that trips within the grid are uniformly distributed. At the intersection of each grid and its associated buffer, each trip is converted into a potential bicycling trip with a calculated probability. This probability is determined based on the relative proportion of buffers within the grid. Second, the buffer size is limited by the data format, and 150 m was selected. Although this is close

to the 100 m standard used in most studies, it is still based on our inference. Additionally, when screening metro-related DBS, the range of connecting DBS between metro stations outside the city and those in the city center may vary. Therefore, we believe it is necessary to conduct a sample survey around metro stations in different city areas to determine this range accurately. Central urban areas and suburbs, as well as different types of functional areas, are necessary places to investigate. Third, our judgment of whether a DBS is related to the metro is solely from a spatial perspective. Employing dynamic judgment based on time and space could provide a more accurate depiction of the connection. Finally, our discussion of the interaction between bike-sharing and the metro is limited to mobility perspectives. Future studies could benefit from more detailed investigations integrating passenger flow data to evaluate the relationship between bike-sharing and the metro system. Firstly, conducting sampling surveys around metro stations in various functional zones would help accurately determine the range of connections between bike-sharing and the metro. This effort would contribute to establishing the boundaries of the metro's influence zone by precisely identifying the starting and ending points of bike-sharing trips. Second, inferring the purposes of bicycle trips could be achieved through analysis of land use types around subway stations. Understanding whether trips are for commuting, leisure, or other purposes based on surrounding amenities and activities would provide deeper insights into travel behaviors and preferences. Finally, correlating station passenger flow data with the timing of bicycle locking and unlocking events could reveal dynamic linkages between bike-sharing and the metro. This analysis would help elucidate how different trip purposes align with metro usage patterns, potentially identifying opportunities for enhancing integration and service efficiency. By integrating these approaches—sampling surveys, land use analysis, and passenger flow correlation—future research can provide a comprehensive understanding of how bike-sharing with different trip purposes interacts with and complements the metro system. This holistic approach would inform urban planning and transportation policies aimed at promoting sustainable and integrated urban mobility solutions.

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