Analysis of Behaviour Pattern of Bicycle-sharing Users Based on Complex Network: a Case Study of Beijing Downtown Area

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Abstract

The introduction of the Bicycle-sharing System (BSS) has provided great convenience for residents for short travel in city. However, the parking lot planning and bicycle logistics distribution remain suboptimal, adversely affecting traffic order. Studying the spatial and temporal usage patterns can be helpful for better management of BSS. In this paper, we propose an analytical framework for detecting the bicycle-sharing pattern based on the community detection algorithms from complex networks to study the spatial-temporal patterns of usage.

Firstly we identify the potential demand for bicycle among urban residents with a dataset from the BSS in Beijing downtown area. Then we construct a linkage network for modelling the BSS by applying community detection algorithms to identify regions of both high and low connectivity. Following this, based on the division of sub-areas, three indicators (graph density, cross-area travel demand, and confidence ellipses) are established for characterizing these sub-areas. Our findings include: (1) The usage pattern of the BSS within the downtown area consistently exhibits relatively stable clustering phenomena over time. (2) The usage pattern is related to the urban spatial structure, with significant differences between weekdays and weekends. (3) Residents tend to complete their cycling within the current sub-areas. (4) Generally, smaller sub-areas tend to have denser bicycle travel behaviour. These insights are vital for improving BSS parking lot planning and logistics distribution.

1. Introduction

In recent years, Bicycle Sharing Systems (BSS) have emerged as a novel, eco-friendly solution for short-distance travel, garnering increasing attention and support in countries such as the United States, Australia, and Canada(Chen et al., 2022). These systems, reliant on fixed docking stations, have been instrumental in promoting sustainable urban mobility. However, their dependence on designated docks can inadvertently give rise to a "last mile" problem, impacting the seamless integration of bicycle sharing into the broader transportation network. Since 2014, China has led the innovation in this field with the introduction of dockless BSS, a groundbreaking approach supported by internet technology that eliminates the need for bicycle docking stations(Gu et al., 2019). The updated BSS service facilitates convenient shared transportation for short urban journeys, connecting individuals' residences or workplaces with metro and bus stations, thus providing seamless door-to-door transit (Yu et al., 2020). This system significantly boosts urban operational efficiency and presents a viable solution to the "last mile" challenge in city transportation.

Advocating for the widespread adoption and promotion of BSS in urban offers numerous benefits, including improved travel efficiency for residents and the creation of cleaner environments. However, the issue of uneven spatial-temporal distribution is exacerbated by inadequate planning of parking facilities and poorly organized bicycle layouts. This severely impacts user experience and hinders the smooth operation of the city. In certain situations, the availability of bicycles exceeds the actual demand. This overabundance, particularly in specific areas, leads to street congestion(Ma et al., 2018), resulting in the wasteful use of public resources and negatively affecting residents' experience. Therefore, analyzing the spatial-temporal patterns of BSS is instrumental in understanding residents' travel behaviours and enhancing service provision. This is beneficial for the sustainable development of cities.

Beijing, as the political, cultural, and economic center of China, is also among the first cities to introduce BSS. The downtown of the city, which includes the Dongcheng and Xicheng districts, plays a vital role in preserving historical and cultural heritage. Situated in the center of Beijing, the downtown is marked by limited space, relatively narrow roads, and a dense population with significant pedestrian traffic. Identifying and detecting the actual patterns of resident demand to enhance the efficiency of BSS services remains an unresolved challenge.

With the advent of mobile internet and cloud computing technologies, the potential for better understanding the urban environments has significantly increased. The resulting geospatial big data is characterized by high spatial-temporal granularity and convenient sources of information, a marked improvement over the traditional method of gathering information through survey questionnaires. Many research has been conducted on the travel data of BSS, covering various aspects such as the integration behaviour between BSS and public transit systems (Yu et al., 2020), demand prediction for bicycles (Y. Li et al., 2015; B. Wang et al., 2022), factors influencing the usage of shared bicycles (Kim, 2018; X. Li et al., 2020), and the spatial-temporal characteristics of cycling behaviour (R. Wang et al., 2022; Yang et al., 2019). However, few studies comprehensively consider cycling behaviour in relation to urban form and structure. BSS datasets, as a form of big data, possess greater universality and accuracy. By employing a data-driven approach, short-distance travel behaviours of groups are captured from the bottom up in both temporal and spatial dimensions. This provides valuable information for mining the spatial-temporal patterns of bicycle travel in cities.

In this paper, we proposed an analytical framework for detecting bicycle-sharing patterns. Our initial study focuses on the analysis and extraction of data from BSS orders, aiming to accurately capture the travel behaviours. These materials are subsequently represented on the constructed grid. Subsequently, we employ community detection algorithm to identify areas characterized by significant cycling activity. To ensure the validity of our divisions, comparative analyses are conducted using various schemes to divide the cycling sub-areas. Three indicators, along with temporal distribution curves, are introduced to describe the spatial and temporal characteristics of the BSS across the identified sub-areas. Applying this method to the downtown of Beijing, it is possible to successfully excavate travel patterns among users and extract the interaction information hidden within the urban structure, solely through BSS data.

The remainder of this paper is organized as follows. Section 2 describes the study area and data. Section 3 presents the methodology of this work, including potential bicycle-sharing behaviour detection, sub-area division, and the bicycle-sharing pattern indicators. Section 4 presents the experimental results, and followed analysis and discussion. Finally, conclusions and future research directions are presented in Section 5. The paper can provide a reference for the better BSS service and urban planning.

2. Study Area and Data

2.1 Study Area

According to the "*Master Plan of Development for Beijing (2016-2035)*", the downtown area of Beijing includes the Dongcheng and Xicheng administrative districts. This region serves as the center for China's political, cultural activities, and international communication, playing a vital role in the protection of historical and cultural heritage and in representing the capital's image. Covering approximately 92.5 km^2, the area has a permanent population of about 1.815 million. It is geographically located between 39°51′ N to 39°58′ N latitude and 116°20′ E to 116° 26′ E longitude. According to the "*Detailed Plan for the Core Area of the Capital City of Beijing (Block Level) (2018-2035)*", the downtown area consists of 32 streets and 183 blocks. The research area is depicted in Figure 1.

2.2 Datasets

2.2.1 BSS Data

The bicycle data used in this study are from the dockless BSS, sourced from the BeiDou Navigation Positioning Service Platform. The dataset includes orders spanning seven consecutive days, with analyses primarily focusing on data from two specific days. The remaining data were used for comparative validation. The two days analyzed were March 24, 2018 (Saturday) and March 26, 2018 (Monday), comprising a total of 1,462,779 bicycle trip records. Each record contains the vehicle number, latitude, longitude, status, and time of the trip. The spatial distribution of these bicycle trips predominantly covers the downtown of Beijing, as depicted in Figure 2.

2.2.2 Geographical Data

(1) The vector boundary data of Beijing's downtown area are sourced from the Alibaba Cloud's DataV.GeoAtlas platform.
(2) The vector data for the division of streets and blocks in Beijing's downtown area come from the website of The People’s Government of Beijing Municipality.

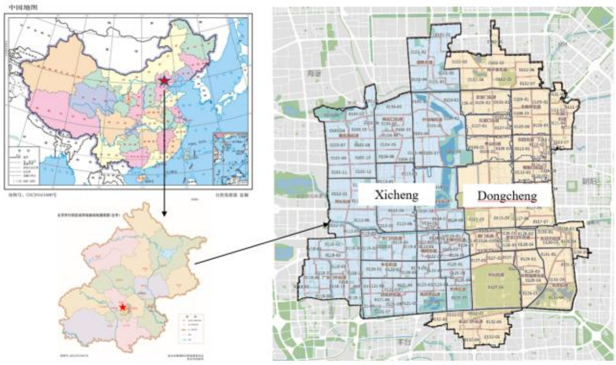


Figure 1. Study area

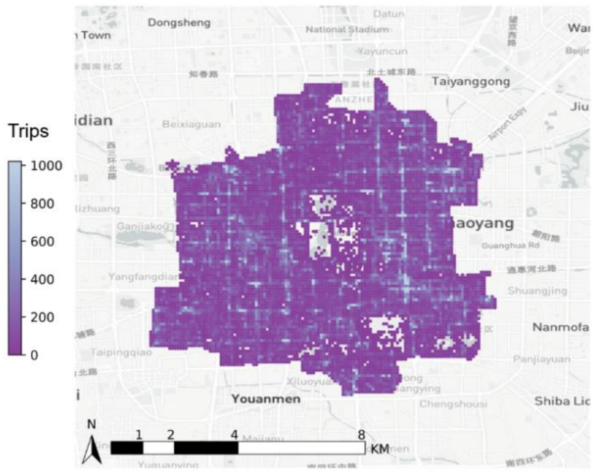


Figure 2. Spatial distribution of BSS data

3. Methodology

3.1 Overall Methodology and Process

As outlined in Figure 3, the modelling process comprises five steps:

(1) Detecting bicycle-sharing behaviours: This step involves selecting data that accurately reflects the temporal and spatial usage patterns of residents' bicycle use, setting the stage for subsequent modelling efforts.
(2) Model construction: Construct a network within the study area, match Origin-Destination (OD) points to the corresponding grid, and aggregate them. Abstract the relationships between bicycle trips into a network of nodes and edges.
(3) Applying the community detection algorithm: Utilize the fast unfolding algorithm to identify areas within the downtown that have a high density of cycling behaviours.
(4) Measuring the structure of the network: Use modularity to measure the density of the divided sub-areas to ensure the optimal result of the area division.
(5) Analysis of bicycle-sharing usage patterns: Validate the results by comparing different cycling sub-area division schemes and introduce indicators for the quantitative analysis of usage patterns.

3.2 Detecting Potential Bicycle-sharing Behaviours

This paper utilizes geospatial big data derived from BSS order data, as detailed in Table 1. This dataset includes information on bike usage, particularly the status of the bike lock. A single journey involves a user starting at an origin point, unlocking a previously parked bike (where the lock status changes from 0 to 1), cycling to a destination, and then re-locking the bike (where the lock status changes back from 1 to 0). This sequence constitutes one complete bicycle-sharing trip.

Through calculating and visualizing the travel distances in the dataset, we extracted shared bicycle trips within a 3-kilometer range, which represents the typical usage scope for the vast majority of users. Based on this assumption, considering a reasonable distance of OD trips inferred from the BSS data, we define the spatial and temporal resolution for which cycling trips can be matched.

On the spatial aspect, a grid is generated consisting of equal-width grid cells, each measuring 50m by 50m, and OD trips are aggregated through the grid. The grid size used in this study was determined after multiple experiments. Appropriate cell size contribute to capturing the flow characteristics of bicycles between regions. While excessively large cells may increase traffic flow, they might obscure interactions between BSS at the neighborhood level within the city. Therefore, the chosen cell size in this study ensures both sufficient travel within cells and comprehensive representation of inter-regional movement.

On the temporal aspect, excessively long biking times in trips might indicate erroneous data records. Assuming the biking time for each trip is Δ, we set the maximum acceptable range at 60 minutes. By detecting bicycle-sharing behaviours, the mesh grids containing the extracted OD points are considered as nodes of the network, and the edges connecting two points are naturally constructed.

When there are more trips with the same OD, the weight of the edge increases. The constructed linkage network can be denoted as $G(V,E,W)$, where V represents the set of nodes, E represents the set of edges, and W represents the edge-weights.

3.3 Revealing of Cycling Areas

Community detection algorithms from the field of complex networks offer an effective method for identifying areas with dense bike-sharing connections directly from BSS data, without the need for additional information. The discipline of complex networks primarily investigates the structure of network systems composed of a large number of interacting nodes and reveals hidden information such as the structural features of the network and dynamic processes. Community detection methods are among the widely recognized approaches suitable for studying complex networks. They can reveal correlations between implicit information resources, fully mine the intrinsic structure within the network, and identify tightly connected groups of nodes, which are referred to as "community". Within a community, the connections between nodes are relatively tight, while the connections between nodes from different communities are less frequent. Various methods have been developed to discover community structures within networks. Given the large scale characteristic of networks constructed based on geospatial big data, the efficiency of community detection algorithms is significantly challenged. Aiming for an approach that is also perfectly applicable to large-scale networks, this study adopts the fast unfolding algorithm (Blondel et al., 2008).

Bike id	Area code	Longitude	Latitude	Status	Time
42749738	110101	116.391146	39.907457	0	2018-03-24 00:00:04
19571059	110101	116.406359	39.916268	0	2018-03-01 00:00:08
17016899	110102	116.355734	39.893544	1	2018-03-05 08:48:43
106607757	110102	116.371922	39.890631	1	2018-03-12 21:41:00
106674679	110102	116.331205	39.920799	1	2018-03-26 18:12:58

Table 1. Examples data of the BSS

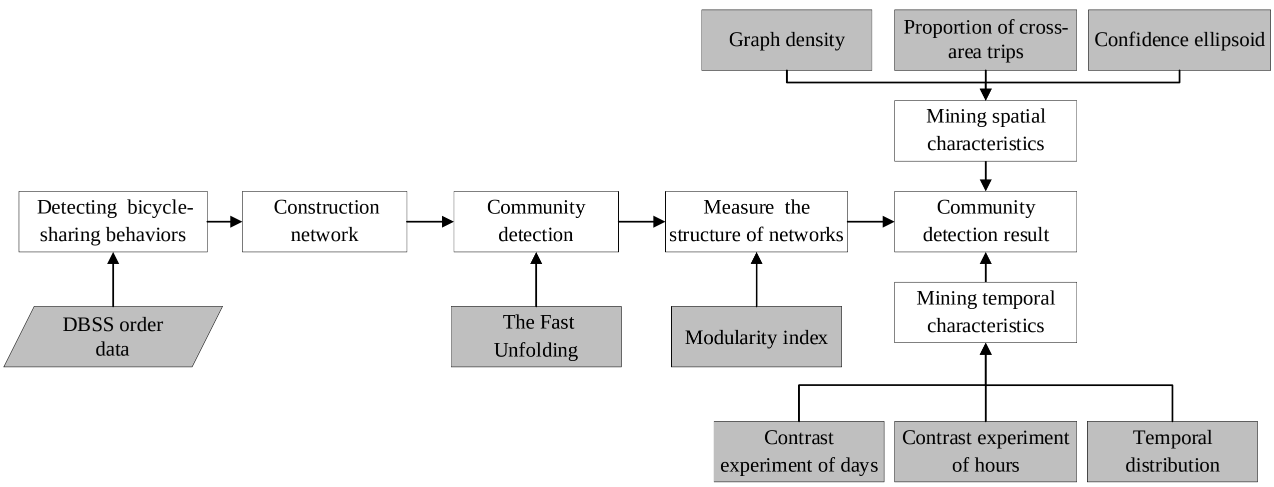


Figure 3. Flowchart of the study

The key points of the fast unfolding algorithm is the optimization of modularity. Modularity is a benefit function that measures the density of edges inside communities compared to edges between communities(Girvan & Newman, 2002). If the modularity is high, it can be interpreted as the community detection algorithm successfully grouping nodes into communities with tighter connections (Rustamaji et al., 2024). Conversely, the resulting modularity is low. The formulation can be denoted as:

$$Q = \frac{1}{2m}\sum_{i,j}[w_{ij} - \frac{k_i - k_j}{2m}]\delta(c_i, c_j) \tag{1.}$$

Where Q represents the modularity, w_{ij} is the weight of the edge between nodes v_i and v_j, k_i is the sum of the weights of the edges connected to node v_i, c_i is the community assigned to node i, and $\delta(u,v) = 1$ when $u = v$, otherwise $\delta(u,v) = 0$.

To quickly maximize modularity, the fast unfolding algorithm employs two iterative steps that are repeated:
Step 1. Modularity Optimization. This step initially treats each node as a separate community. It then reassigns each node to the community of its adjacent nodes, using the increase in modularity before and after the reassignment to determine whether to complete this step of the division.
Step 2. Community Aggregation. After traversing all nodes in the network, all nodes belonging to the same community are treated as a single new node, and Step 1 is repeated.

These two steps are iterated continuously until the modularity achieves an optimal result and ceases to increase, at which point the calculation stops, yielding the division result of closely connected sub-areas.

3.4 Indicators for the Bicycle-sharing Patterns

To describe bicycle-sharing patterns more accurately, this study employs three indicators to analyze and characterize bicycle usage within sub-areas.

3.4.1 Graph Density:

In network science, graph density is an index to measure the density of edges within a network. Through the graph density metric, one can understand the proportion of actual to potential edges within sub-regions, thereby quantitatively characterizing the degree of connectivity within the network. It is defined as Equation (2):

$$D_k = \frac{2m}{n(n-1)} \tag{2.}$$

In which n represents the number of grids in a sub-region, and m represents the number of edges within a sub-region. A higher D_k indicates more dense network connectivity within the sub-region, a higher frequency of bicycle usage, and an increased demand for transportation connectivity within the area.

3.4.2 Proportion of Cross-area Bicycle-sharing Trips:

By extracting trips within subareas where both origin and destination (OD) are inside the area Q_{inside}, trips with only the destination (D) inside Q_{in}, and trips with only the origin (O) inside Q_{out}, the proportion of cross-regional bicycle-sharing trips is calculated. The calculation formula is given by Equation (3):

$$P_k = \frac{Q_{in} + Q_{out}}{Q_{in} + Q_{out} + Q_{inside}} \tag{3.}$$

A higher value implies that, compared to intraregional trips, the proportion of trips entering into and exiting from the region is greater. In other words, a higher value indicates a larger proportion of interactions between the region and external areas among all trips, which implies a higher demand for rebalancing bicycles between different subareas.

3.4.3 Spatial Distribution Patterns of Bicycle Usage:

The study employs 95% confidence ellipses to characterize the spatial distribution of bicycle trips within sub-communities, where the length of the ellipse's major axis a and the length of its minor axis b represent the direction of data distribution and the scope of demand distribution, respectively. The size of the ellipse indicates the area of concentrated bicycle demand; the ellipse's flatness measures the difference between the major and minor axes, describing the spatial orientation of the demand distribution area, as calculated by Equation (4):

$$O_b = \frac{a-b}{a} \tag{4.}$$

When the confidence ellipse's flatness approaches zero, it indicates that bicycle usage is distributed more evenly across different directions; a greater flatness signifies a higher directionality in cycling demand, with a majority of citizens using shared bicycles in similar directions.

4. Results and Discussion

4.1 Results of Community Detection

4.1.1 Result of Cycling Sub-area Division

By applying the aforementioned method to the dataset, we identified 28,598 nodes and 210,011 edges on the 24th (Saturday), and 30,034 nodes and 281,967 edges on the 26th (Monday), leading to the construction of two linkage networks. The fast unfolding algorithm, iterated twice on both networks, achieved maximum modularity values of 0.66105 and 0.65996, respectively. Modularity is a metric that ranges from [-1, 1] (Gouvêa et al., 2021), and in practical network analysis, it typically falls between 0.3 and 0.7. This indicates that the fast unfolding algorithm successfully and reliably identified densely used areas within the bicycle-sharing network. The increasing number of nodes and edges suggests a higher quantity and likelihood of bicycle usage during weekdays. The decreased modularity of the linkage network suggests that residents' travels encompass more dispersed popular locations, reflecting differences between weekdays and weekends. Consequently, it is evident that the role of the BSS in connecting the "last mile" of urban transportation is more pronounced on weekdays.

Figure 4 visually depicts the two linkage networks; the blue lines represent trips between two nodes, with darker shades indicating higher traffic volumes. The diagram illustrates that the utilization of shared bicycles creates patterns resembling diverging rays that connect surrounding neighborhoods. This pattern is consistent across both weekdays and weekends, displaying distinct clustering characteristics and relatively stable structures, with higher trip volumes observed on weekdays compared to weekends. It is noteworthy that some areas, marked with red circles, show inconsistencies. This variation can be attributed to a higher proportion of commute-related trips during workdays.

As depicted in Figure 5, the downtown area is segmented into nine sub-areas on both analyzed days, with each sub-area averaging 3,171 and 3,330 mesh grids, covering 7.92 km² and 8.33 km² respectively. Overlaying the sub-community divisions with the downtown boundaries reveals a high degree of correspondence. This indicates a significant relationship between the spatial usage patterns of shared bicycles and the urban layout. This alignment suggests that the arrangement of BSS facilities within these areas is logically structured, enhancing the efficiency and convenience of urban travel. The high match rate underscores how resident travel habits and route selections are intricately linked to the street layout, affirming the integral role of spatial planning in influencing mobility patterns within the city.

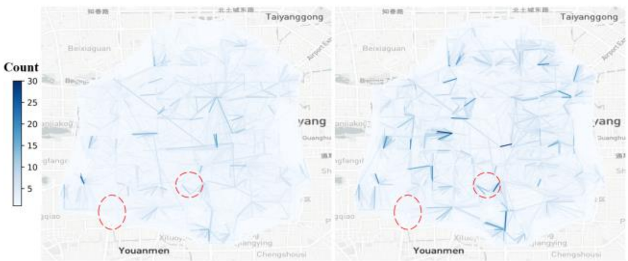


Figure 4. Linkage networks displayed (a) 24th (b) 26th

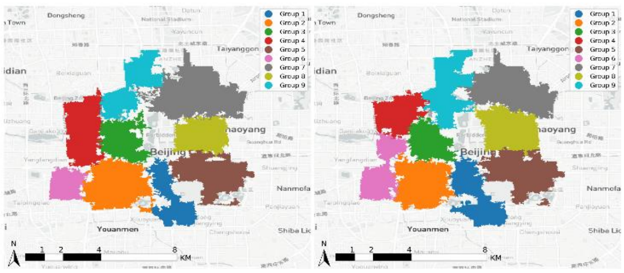


Figure 5. Division of sub-areas (a) 24th; (b) 26th

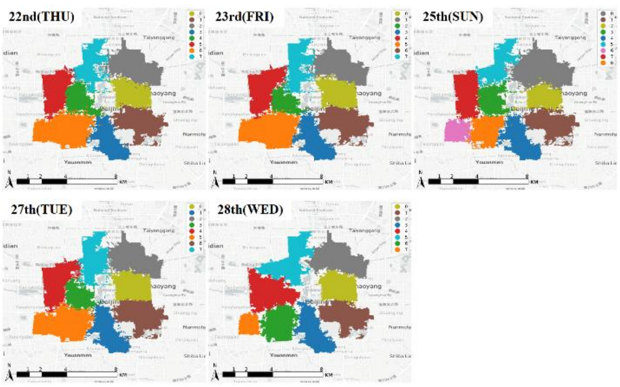


Figure 6. Comparison of other dates by community detection

4.1.2 Comparisons on Different Division Schemes

(1) Comparative analysis over different days. This study employed community detection techniques based solely on BSS data to identify highly interconnected regions within a network of links. The reliability of this approach is significantly influenced by the quality of the data used. To validate the accuracy of the identified areas, BSS data from five additional days (the 22nd, 23rd, 25th, 27th, and 28th) were analyzed to evaluate the logic of the partitions. For each of these days, distinct connection networks were constructed, and the fast unfolding algorithm was applied to reveal areas of strong connectivity. The modularity values obtained from these analyses consistently ranged from 0.65 to 0.67, indicating significant clustering patterns in the usage of shared bicycles, which were persistent across both weekdays and weekends.

Figure 6 displays the results of the cycling community divisions in five sub-figures ordered by date. It highlights the clustering pattern in the daily usage of BSS, showing only minor variations. The high consistency in cycling area divisions across different dates underscores the effectiveness of this method in delineating spatial structures from the BSS in downtown Beijing. Notably, the three communities within the Dongcheng district on the eastern side exhibited remarkable stability, with little variation in patterns between weekdays and weekends. These areas are characterized by a dense mix of residential and commercial functions—including housing, shopping centers, leisure, and cultural facilities—which ensures that the travel behaviours of residents are not significantly influenced by whether it is a workday or a rest day. This blending of functions supports a consistent level of mobility regardless of the day of the week. Consequently, similar travel demands and behavioural patterns are observed during weekdays and weekends, with minimal changes in community morphology.

However, an exception was noted on Sunday, the 25th, when the cycling linkage network was divided into 9 sub-areas, compared to 8 on the other dates. On the 24th, 25th, and 28th, Guang'anmen Outer Street was categorized as a distinct area. This differentiation reflects notable variances in the residents' lifestyle rhythms and scopes of activities between weekdays and weekends, potentially due to a higher density of residential zones in this area. On weekdays, the frequent interactions with adjacent communities for work, schooling, and other activities often result in the integration of this street with neighboring communities into a single sub-area. Conversely, on weekends, the inclination towards localized leisure activities led to its recognition as an independent sub-area.

(2) Comparative analysis over different periods. To ensure the precision of temporal sub-area divisions, this study conducted a statistical analysis of bicycle usage over 24 hours on the 24th and 26th. The daily cycle was segmented into four distinct time periods based on the volume characteristics of bicycle usage (Chai et al., 2021): morning (05:00-09:00), noon (10:00-14:00), afternoon (15:00-19:00), and night (20:00-04:00). For each day, sub-networks corresponding to these time slots were created, and community detection algorithms were subsequently applied. The results are presented in Figure 7, with panels (a) and (b) displaying the cycling sub-areas on the 24th and 26th, across the four time periods, respectively.

Segmenting the data into these time periods provides a more granular insight into residents' travel behaviour. Figure 7 confirms that the usage of shared bicycles consistently shows a clustering pattern, which is robust across different days and times within a day, corroborating the trends observed in Figure 5. On the 24th, variations in sub-areas structures at different times are evident, with denser clusters during the noon and afternoon periods (10:00-14:00 and 15:00-19:00) suggesting more active or clearly defined communities. In contrast, the morning (05:00-09:00) and night (20:00-04:00) intervals exhibited more dispersed and indistinct cycling area configurations.

On the 26th, a similar trend is observed but with a notable distinction in the morning segment. The cycling sub-areas during this time appear more compact and well-defined compared to the 24th, likely reflecting the morning rush on workdays when BSS is heavily utilized for commuting purposes within a concentrated time period. This analysis not only underscores the variability of community structures based on time but also highlights how these structures can vary significantly on workdays versus weekends, thereby providing valuable insights into the dynamic usage patterns of shared bicycles.

4.2 Analysis of Bicycle-sharing Pattern

4.2.1 Discussion of the Blank Areas

The identification of underutilized areas within sub-regions, as delineated by community detection algorithms, is primarily due to the low frequency of bicycle use in these zones. These areas were identified through visual analysis and corroborated by survey studies. An analytical overlay of these sub-regions on maps showed that boundaries change minimally, primarily reflecting variations in cycling habits between weekdays and weekends. The demarcation of community borders is largely influenced by natural barriers such as rivers and parks. Notably, regions including the Forbidden City and similar locales, which are highlighted in Figures 8(a), (b), and (c), are characterized by their restricted access, making them unsuitable or prohibited for cycling and thereby naturally forming the peripheries of sub-areas.

Moreover, urban expressways and major thoroughfares, such as Gulou Outer Street and analogous areas depicted in Figures 8(d), (e), and (f), act as significant obstacles. These barriers, with their complex traffic flows and crossing difficulties, impede bicycle mobility. Addressing these obstructions within the downtown area could substantially improve cycling conditions and meet the varied cycling needs of the residents, thereby enhancing the overall utility and accessibility of the BSS.

4.2.2 Discussion the Indicators of Bicycle-sharing Patterns

Figure 9 illustrates the usage patterns of shared bicycles within each sub-community on the 24th (panels (a)-(d)) and the 26th (panels (e)-(h)), detailing metrics such as graph density (D_k), bicycle-sharing potential ($Q_{in}, Q_{out}, Q_{inside}$), cross-area travel demand (P_k), and the temporal distribution characteristics of bicycle usage. This multidimensional approach provides insights into the usage patterns from both spatial and temporal perspectives.

Initially, a horizontal comparison of indicators within a single day reveals that D_k, shared bicycle potential, and P_k are mutually independent. This aids in providing a reliable basis for comprehensive analysis in subsequent stages. As observed in Figures 9 (b) and (c), although some areas have similar numbers of bicycle-sharing potential internal trips (Q_{inside}), the level of their cross-area travel demand (P_k) may vary. In practice, such scenarios should be managed with different policies. For example, in sub-areas 1 and 3 on 24th, despite having similar Q_{inside}, the P_k varies significantly. In cases of lower P_k, governments or companies could implement policies to restrict cross-area bicycle-sharing trips. This approach could reduce the workload for vehicle rebalancing without hindering residents' access to bicycles. However, in areas such as sub-areas 1, 3, 8, and 9 on 24th, which have a high proportion of cross-area trips, implementing the same policy could inconvenience users. Therefore, developing dynamic scheduling and pricing policies based on the P_k could offer a solution for providing a higher quality BSS.

A horizontal comparison within a single day shows that D_k, bicycle-sharing potential, and P_k are mutually independent, which forms a solid foundation for a more detailed subsequent analysis. As seen in Figures 9(b) and (c), while some areas might report similar internal bicycle-sharing potential (Q_{inside}), their cross-area travel demands (P_k) could differ markedly. Such disparities necessitate differentiated policy interventions. For instance, in sub-areas 1 and 3 on the 24th, despite comparable Q_{inside} values, the significant variance in P_k suggests tailored strategies; lower P_k might prompt the implementation of restrictions on cross-area bicycle-sharing trips to streamline vehicle rebalancing, thereby maintaining access without imposing undue logistical burdens. Conversely, for areas like sub-areas 1, 3, 8, and 9 on the 24th, which experience high volumes of cross-area trips, such restrictive measures could adversely affect user convenience. Here, adaptive scheduling and dynamic pricing based on P_k values could enhance service quality and user satisfaction in high-demand zones.

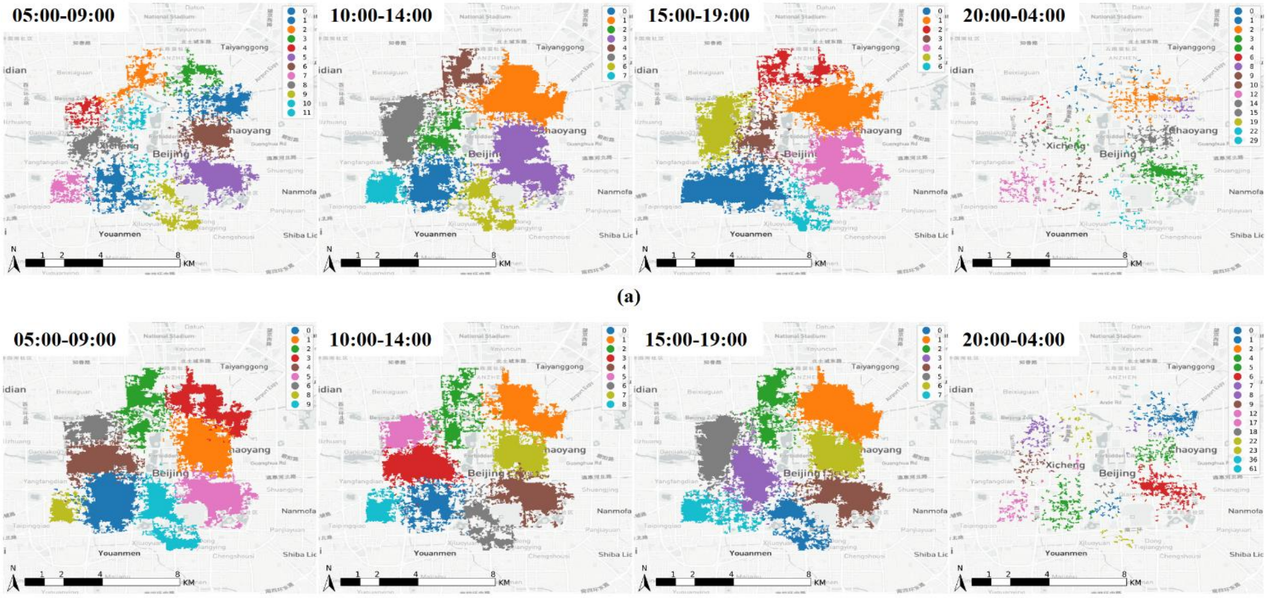
Analysis of Figure 9(a) and (e) shows that on the 24th, sub-area 6, and on the 26th, sub-areas 3 and 4, exhibit higher graph densities (D_k), suggesting concentrated user activities in these smaller areas at certain times. However, the correlation between small area size and high graph density is not always consistent, as demonstrated by sub-area 3 on the 24th.

Temporal dynamics of bicycle usage also provide critical insights into the operational characteristics of BSS schemes. The usage trend curves from Figures 9(d) and (h) reflect distinct patterns on the 24th and 26th. The 24th shows an even distribution of bicycle usage from 8 a.m. to 5 p.m., indicative of non-commuter or leisurely travel patterns. In stark contrast, the 26th reveals a tidal usage pattern with peaks around traditional commuting hours (06:00-08:00 and 16:00-18:00), underscoring the BSS's role in facilitating daily commutes.

Spatial distributions were similarly analyzed, with 95% confidence ellipses employed to clarify the spatial distribution of bicycle travel within communities, particularly focusing on sub-area 2 as depicted in Figure 10. The scatter plot, which uses points at 25% transparency to highlight denser usage areas as brighter, indicates that weekend bicycle travel in this sub-area tends towards greater directionality (higher O_b value) and variability in travel directions compared to weekdays. This intriguing trend may be linked to local preferences. For example, residents near Niujie Street tend to favor trips towards Tiantan Street on weekends, while the increased weekday traffic on Yuetan Street likely relates to its employment opportunities. This illustrates how BSS adapt to and support the varying daily rhythms of urban life.

5. Conclusions and Future Work

Extracting residents' travel patterns and uncovering urban spatial correlations from large-scale BSS data has consistently been at the forefront of research interests. This article introduces an analytical framework designed to uncover spatial-temporal usage patterns from BSS data. This framework aims to support improved BSS services and urban planning. It comprises three main components: detecting potential bicycle-sharing behaviours, revealing cycling areas, and indicators for bicycle-sharing patterns. Community detection algorithms enable the identification of interactive behaviours in city-wide bike-sharing usage from a broader perspective. Building on this, the bike-sharing travel pattern indicators provide detailed characteristics of sub-areas with distinct travel features, including graph density, cross-area travel demand, and confidence ellipses, which are crucial for a better understanding of the internal structure of cities.



(a)

(b)

Fig 7 Community detection results based on time period segmentation. (a)24th; (b)26th

Using the method proposed in this paper, the following was discovered:

(1) The arrangement of BSS facilities within Beijing's downtown is considered to be relatively reasonable. The usage pattern of BSS within the downtown area consistently exhibits a clustering phenomenon over time.
(2) The clustering pattern of BSS in the downtown is relatively stable, with only minor changes. Compared to Xicheng, the clustering pattern in Dongcheng is more stable, likely due to the dense combination of residential and commercial functions in the area.
(3) The usage of BSS in downtown is mostly affected by natural barriers such as rivers and parks, and some areas are affected by urban transportation infrastructure. However, the latter effect is attenuated during weekdays.
(4) Residents tend to complete their cycling trips within the designated sub-areas. Furthermore, compared to non-working days, the role of BSS in bridging the 'last mile' of urban transportation is more pronounced on working days.
(5) The inter-area travel demands vary between different sub-areas, necessitating diverse BSS management strategies.
(6) Generally, smaller sub-areas tend to have denser bicycle travel behaviour.

Further analysis will be devoted to following directions. For instance, to deepen the understanding of urban residents' travel motivations, integrating BSS data with information from bus and subway systems is crucial. Posteriorly, to tailor BSS more effectively to local needs, merging data from land use, urban economics, and survey questionnaires is recommended. Additionally, our study utilized only three indicators, omitting factors like weather variations and special events. Expanding the range of indicators in future studies would enhance our insights. These efforts lay a research groundwork for enhancing urban BSS services and planning, thereby supporting the sustainable development of city environments.

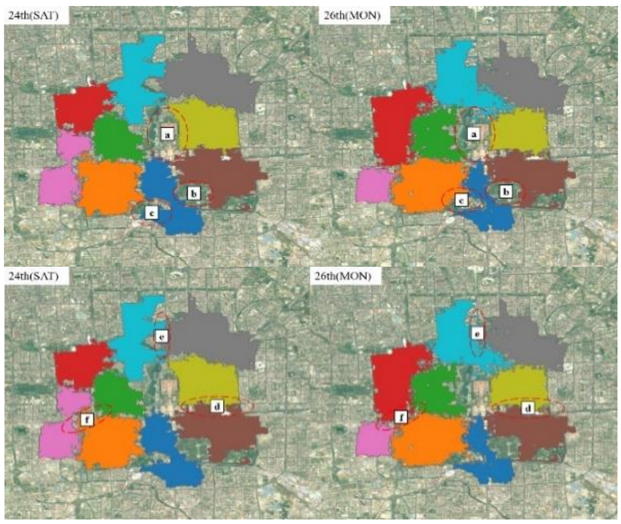


Figure 8. (a) The Forbidden City and Beihai,Zhonghai,Nanhai; (b) Temple of Heaven; (c) Taoranting Park; (d) East Chang'an Street (e) GuLouWai Street ;(f) West Second Ring Road Viaduct

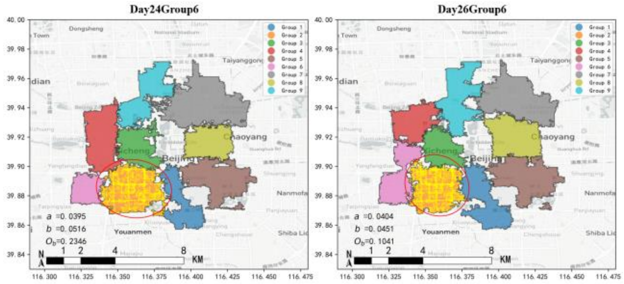


Figure 10. Spatial distribution of bicycles usage pattern

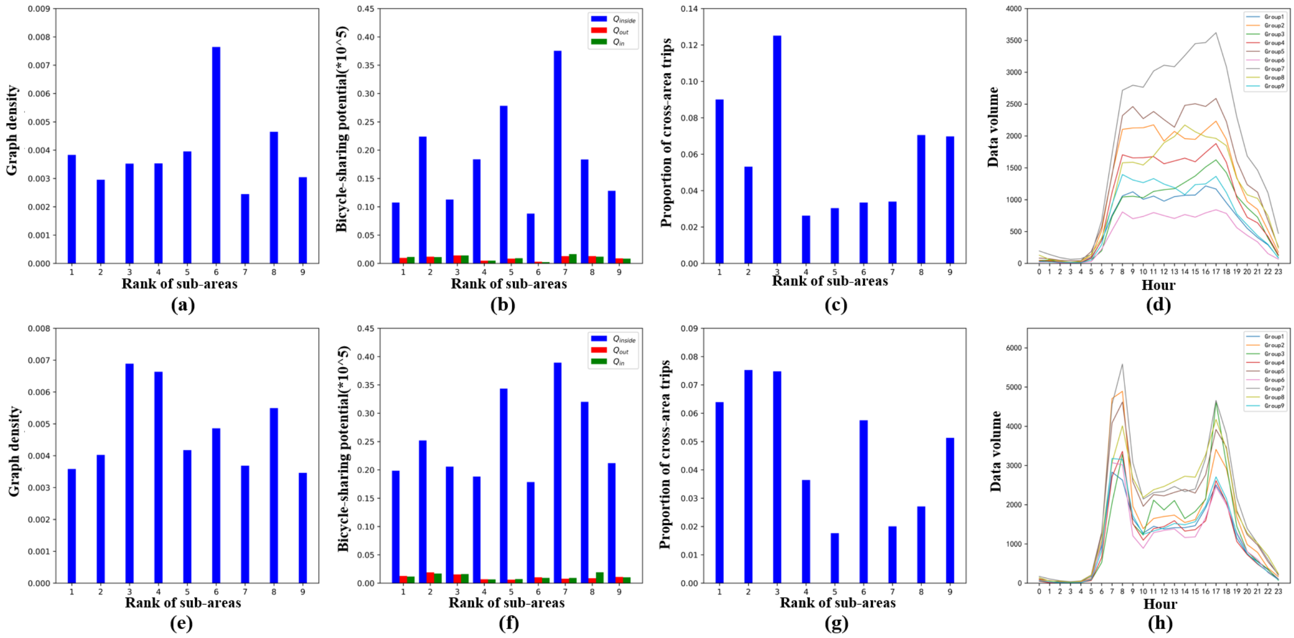


Figure 9. BSS usage pattern: (a),(b),(c),(d) on 24th and (e),(f),(g),(h) on 26th

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