applied sciences

Article

Operation Characteristics of a Free-Floating Bike Sharing System as a Feeder Mode to Rail Transit Based on GPS Data

Juchen Li and Xiucheng Guo *

Jiangsu Key Laboratory of Urban ITS, School of Transportation, Southeast University, No. 2 Dongnandaxue Road, Nanjing 211189, China
* Correspondence: seuguo@163.com

Abstract: The jobs-housing imbalance and long commuting distances for residents in many megacities in China are promoting the increase in mode share with rail transit. The emergence of free-floating bike sharing (FFBS) provides an attractive and cost-effective multi-modal solution to the first/last mile problem. This study identifies the mobility patterns of free-floating bikes as a feeder mode to 277 rail transit stations in Beijing using detailed GPS data, and the relationships between these patterns, culture and spatial layout of the city are examined. The results show that the distribution of free-floating bikes, as a feeder mode to rail transit, exhibits an aggregating feature in the spatial-temporal pattern on weekdays. According to the results of the Clusters method and ANOVA analysis, the operation characteristics of free-floating bikes are related to the location of the transit station and the job-to-housing ratio around that area, and imbalanced usage of shared bikes across the city may result from the extreme values of job-to-housing ratios. Based on the fitted distance decay curve, accessing distance is greatly influenced by urban morphology and location. Based on these findings, recommendations for planning, management, and rebalancing of the FFBS system as a feeder mode to rail transit are proposed to promote the integration of FFBS and the rail transit system.

Keywords: free-floating bike sharing; operation characteristics; GPS data; rail transit; integration

check for updates

Citation: Li, J.; Guo, X. Operation Characteristics of a Free-Floating Bike Sharing System as a Feeder Mode to Rail Transit Based on GPS Data. *Appl. Sci.* **2022**, *12*, 8677. https://doi.org/10.3390/app12178677

Academic Editor: Sakdirat Kaewunruen

Received: 8 July 2022
Accepted: 27 August 2022
Published: 30 August 2022

1. Introduction

Chinese cities have been experiencing drastic market transitions and rapid restructuring of urban space in recent years. The expansion of suburbanization forces residents to move from the city center to the suburbs, while large numbers of jobs remain in the central area [1]. The widespread occurrence of home-work separation has led to increases in the commuting distances of residents, resulting in the rise in mode splitting in rail transit [2]. Due to their significant construction and operation costs, rail transit systems are usually less extensive in the suburbs, and thus, are unable to offer people door-to-door service [3]. It is a common situation that commuters may have difficulty getting from an urban rail transit (or their starting location) to their final destination (or a transportation network); this scenario is alternatively known as the last (or first) mile problem. Considering that transfer is often stressful and time-consuming [4], the smooth operation of urban rail transit depends on effective multimodal solutions that solve the first/last mile problem. Bike sharing has gradually become an important mode for commuters [5,6], which offers an attractive and cost-effective solution to the first/last mile problem [7]. Integration of bike sharing and rail transit can lower travel costs and improve the quality of urban space [8], making rail transit more convenient and potentially improving the demand for bicycle and rail transit [9].

Since the outbreak of COVID-19, travel demand and transmission risk have become the main concerns in residents' travel decisions, and bike-sharing has been greatly impacted. After a period of usage falls due to the city-wide lockdowns or suspensions of bike-sharing services in the early stage of the pandemic [10], in the post-COVID period in some cities, the number of shared bike riders has grown progressively compared with other transport modes [11,12]. Residents may choose the bike-sharing mode to avoid public transport and maintain social distance. Despite the changes in user volume, usage patterns, and motivations [13,14], the bike-sharing mode is considered the most robust and resilient transportation option during the post-coronavirus era [15] and is an area of strong research focus.

There are two main types of bike-sharing systems: station-based bike sharing (SBBS) and free-floating bike sharing (FFBS). FFBS does not have fixed dock stations. Thus, expensive construction costs for stations and kiosk machines can be avoided. Users can unlock the shared bikes by simply using their smartphone, and the bikes can be left anywhere in public for the next user. Compared with SBBS users, the average walking distances of FFBS users are shorter. People can track down bikes nearby before the trip by checking the mobile app whenever they need service, which frees them from worries regarding whether there are bikes available in the public bike station. When reaching the destination, users can leave bikes near the destination without concerns about potential shortages of vacant spots in the station, which is attractive for commuters with limited time and travelers new to the area [16,17]. However, new problems also occur, such as illegal parking, vandalism, and imbalance problems. Due to the imperfect management and inadequate regulations, the expansion of bike sharing occupies limited urban spaces, adding to the congestion and the decline in the quality of urban space. The uneven distribution of FFBS flows also results in imbalance problems, making it difficult for users to find available shared bikes during peak hours. For instance, in the Sihui subway station in Beijing, thousands of bikes were parked around the station during rush hours, which occupied all the non-motorized space and an entire motorway, resulting in a large waste of public space and idle bikes. Conversely, suburban areas far from the city center often suffer from a short supply. Rebalancing shared bikes in the system is essential to fulfill commuter demand at different locations at different times. Compared with SBBS, the rebalancing operation of FFBS can be more challenging, as numerous scattered stations rather than fixed stations exist in this system, leading to higher operations costs [18]. These problems may influence bike-sharing users' safety and satisfaction, and challenge urban planning and transportation management. To improve the service quality and operation efficiency of FFBS, it is important to identify the causes of these problems by considering the following questions: Why does the imbalanced usage of bike-sharing as a feeder mode of rail transit occur? What are the spatial and temporal characteristics of these bike-sharing trips? What factors may influence the distribution of bike-sharing flows to rail stations? How can we improve the management of the bike-sharing system based on these revealed characteristics? This paper investigates and seeks to provide answers to these researchquestions.

In China, the use of the mobile app-based smart lock equipped with GPS in the FFBS system makes it possible to acquire the entire sample data. Large amounts of data can be sensed and analyzed to uncover the operation patterns of FFBS and offer methods of smart management [19]. This study analyzed the operation characteristics of FFBS as a feeder mode to 277 subway stations in Bejing for a week. In the following sections, we proceed with a literature review of previous research on the connection between bike sharing and rail transit. Data collection and cleaning are described in Section 3. Based on a detailed GPS-Data analysis for the Mobike, temporal and spatial patterns are identified in Sections 4.1 and 4.2. Section 4.2 presents the results of cluster techniques and ANOVA analyses used to investigate how usage patterns of FFBS as a feeder to rail transit are shared across urban morphology and geographically distributed of subway stations in the city. The relationships between urban morphology, spatial layout, and accessing distance are also explored in Section 4.3. Finally, strategies for FFBS planning, parking, rebalancing and management around rail transit in Beijing are discussed in Section 5. This research revealed not only the operation characteristics of FFBS as a feeder mode to rail transit, but also how these patterns relate to and reflect the city's culture and spatial layout. The research results can contribute to a reasonable rebalancing of bike sharing and rational spatial layout around rail transit, integrating bike sharing and rail transit in an efficient way.

2. Literature Review

As an environmentally friendly transportation mode in urban cities, bike sharing can improve the sustainability of urban transport [20]. After decades of practical and theoretical research, scholars have investigated the planning, operation, and management of bike sharing from different aspects, among which the usage pattern and operation characteristics are the basis of improving bike sharing systems. For example, Xing, Wang and Lu studied the spatial distribution of the bike-sharing usage patterns of five typical activities [21]. Due to the obvious fluctuations in bike-sharing operations, many studies focus on the rebalancing of bike-sharing. In the short term, the rebalancing depends on operators using vehicle fleets to move bikes between different locations. Previous studies proposed models for the pickup and delivery vehicle routing problem [22,23]. In addition, user-based rebalancing operations were performed, classified as static and dynamic approaches [24,25]. It is apparent that research on FFBS characteristics and rebalancing is limited compared with that on SBBS.

With the development of urban rail transit systems in recent years, the combination of bike sharing and rail transit has become an important research focus. Fishman suggested that "improved public transport integration" be treated as an important research direction in the future when studying bike sharing [26]. Feng, Affonso and Zolghadri investigated the famous bike sharing system Vélib and noted that the well-organized combination of bike sharing and rail transit could improve their use [27]. The research conducted by Martin and Shaheen observed that bike sharing had different influences on rail transit in different areas based on the development intensity. In an area with low development intensity, bike sharing mainly functions as a feeder mode for rail transit, whereas in dense urban cores, it can even replace rail transit by virtue of its advantages in mobility and speed, instead of functioning as a feeder of rail transit only [28]. Ji et al. established mode choice models for public bicycles and private bicycles to quantify the influence of personal and station attributes on users who used public bikes as a feeder mode to rail transit. This study found that female, older, and low-income rail commuters are less likely to use a public bicycle to access rail transit [16]. Faghih-Imani et al. revealed the competition between BSS and car modes in general in dense urban areas [29]. Ma, Liu and Erdogan researched the influence of bike sharing on rail transit in Washington, D.C. and found that when the Cabi passenger flow increases by 10%, the passenger flow of the rail transit increases by 2.8% [30]. Flamm showed that bike sharing could relieve the congestion problem of rail transit compared with having on-board bicycles [31]. Griffin and Sener researched the relationship between bike sharing and rail transit from the perspective of planning objectives and suggested a framework that can integrate them properly [5].

Existing research has examined the operational features of FFBS, but few studies have investigated its operation as a feeder mode to rail transit. In this study, we endeavor to rectify this gap in literature. The analysis of FFBS operational characteristics as a feeder mode will assist researchers to further investigate the rebalancing and repositioning of FFBS and improve the management of urban public transport systems.

3. Study Area and Data

Beijing is one of the largest cities in China with a well-equipped urban rail transit system and an extended rail transit network. In 2018, 22 lines were in operation (including twenty-one metro lines and one airport railway line), covering 11 municipal districts of Beijing and incorporating 370 stations. Moreover, Beijing was one of the first cities to introduce FFBS into the city with 700,000 bikes in May 2017. After the implementation of market regulation and management, 10 bike-sharing enterprises were still operating in Beijing by the end of April 2018, with the total number of operating bikes controlled at around 1.9 million. Among them, Mobike entered the market at the early stage of bike-sharing development in 2016 and was one of the largest bike-sharing companies in China. The patented smart locks on Mobikes are equipped with an integrated GPS and communication module, enabling users to locate and use the nearest bike through the mobile application. In addition, Mobike attracted more potential users by offering shared-bike reservation services. Although its new user registration deposit is relatively higher than other brands due to the higher bike manufacturing costs, Mobike has simplified charging rules. Its daily use price is largely on par with other brands at around 0.5 yuan per hour. Thus, these characteristics enabled Mobike to obtain the highest market occupancy rate (57%) and vehicle utilization (61.9%) before COVID-19. For this research study, we examine Mobikes operating around 277 subway stations in 11 municipal districts in Beijing. We focus primarily on weekday data because weekdays typically correspond to more regular shared bicycling usage patterns [32].

3.1. Data Collection

3.1.1. Mobike GPS Data

These data are derived from the open data provided by Mobike company in the Mobike Cup Algorithm Challenge Match. The initial data cover the whole-day (0:00–24:00) GPS data of Mobikes in Beijing from May 10, 2017 to May 19, 2017, amounting to 2,466,817 data records (Table 1). After desensitization, each datum included seven numeric fields: order id, user id, bike id, bike type, start time, origin Geohash encoding, and destination Geohash encoding. The origin-destination location information is denoted as a 7-bit encoding in the Geohash system, a geocoding system incorporated into the public domain that can be decoded as the latitude and longitude in reverse. The deviation can be ±76 m, which translates into a rectangular region with a side length of approximately 150 m; this is treated as traffic zones for bike sharing in this research study.

Table 1. Data description and sources.

Data Type	Data Description	Amount of Data	Data Sources
GPS data	ordered, userid, bikeid, biketype, startime, geohashed_start_loc, geohashed_end_loc;	2,466,817 records	Open data of Mobike Co., Ltd., Beijing, China
POI data	name, latitude, longitude, address, type	723,154 records	Autonavi map
Track data	OD of each path, direction, distance, trip time	879,158 records	Baidu map

3.1.2. POI Data

Applying internet data capture technology, open data were obtained through the Amap API. The considered objects are the points of interest in Beijing in May 2017, amounting to 723,154 records, each including six numeric fields: name, longitude, latitude, address, type 1, type 2, and type 3.

3.2. Data Cleaning

The original dataset provided by Mobike was filtered to meet the research objective. As the study focuses on bike-sharing and its connection with rail transit, those trips not related to subway stations are outside the scope of this study. Thus, the term "access trip" is introduced here, defined as trips whose endpoints (origin or destination) coincide with the traffic zone where the subway station entrances are located. These access trips were filtered and the other data were discarded. In consideration of the rail network density and critical accessing distance for a cyclist to rail transit [33], the data with excessively small (less than 100 m) or large (greater than 6 km) distances and those with both origin and destination located in the vicinity of subway station entrances (less than 5%) were regarded as abnormal data and discarded. In addition, extreme weather can significantly affect the possibility of commuters choosing cycling mode, so data on the days with extreme weather conditions were also removed. Thus, the data for 17 May was discarded to avoid the influence of stormy weather. Finally, 879,158 GPS data records of Mobikes remained, accounting for 36% of the original data.

3.3. Data Pre-Processing

The filtered data were classified into two types according to whether the trip was from an origin to a subway station or from a subway station to a destination. These two trip types corresponded to 446,635 and 432,523 data records, respectively, which are similar. JavaScript was utilized to decompile the Geohash encoding in these data and obtain the corresponding latitude and longitude. To obtain the track of each shared bike, the route planning function (direction api v1.0) of Baidu Map API is used in this paper. Amounting to 879,158 data records, the cycling track, cycling distance and cycling time of each trip were obtained. It is noteworthy that other web map services that provide time cost with related distance and route information under cycling mode, such as Google Map in western countries and Gaode Map in China, can also be applied.

In the remainder of this paper, "trip from origin" represents a trip by bike-sharing to a subway station, and "trip to destination" represents a trip by bike-sharing from a subway station.

4. Data Analysis

To understand the spatial and temporal characteristics of free-floating bike-sharing usage as a feeder mode to rail transit, an analysis framework is built in this paper, as shown in Figure 1. After the input and processing of the original dataset, bike-sharing trip information was acquired, including the trip OD locations, starting time, cycling track, distance, duration, and urban morphology information. A probability distribution analysis revealed the temporal fluctuation in bike-sharing trips to rail stations. To consider the spatial factor, the kernel-density method was adopted, and the hierarchical clustering technique was applied to rail station classification based on the distribution probability of bike-sharing trips. In addition, the ANOVA method and Tukey test were utilized to study the impact of urban morphology on the usage pattern. Finally, probability density diagrams were constructed to show the accessing distance distribution characteristics.

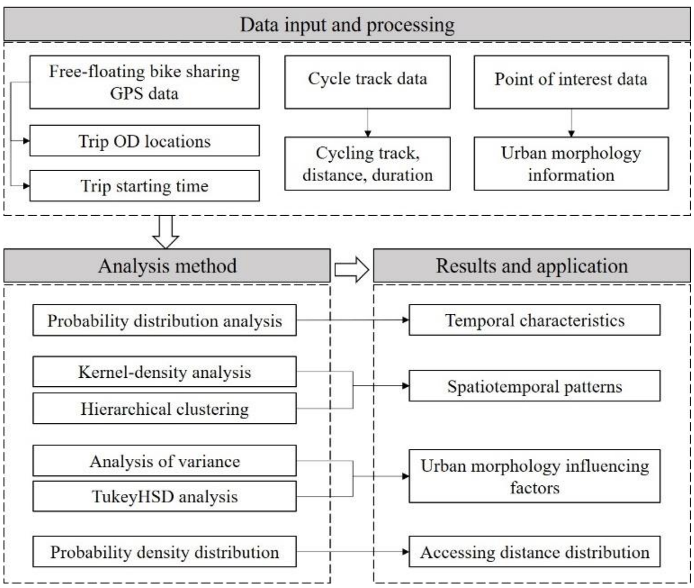
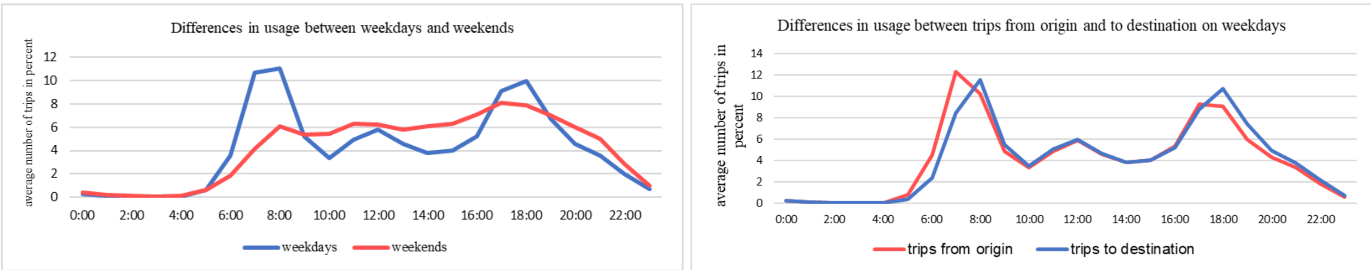


Figure 1. Flowchart for FFBS operation characteristic analysis as a feeder mode to rail transit.

4.1. Temporal Patterns

Probability distribution graphs were generated, and the distribution of service time of Mobikes for accessing rail transit was obtained, as illustrated in Figure 2a. The most significant variation exists between weekdays and weekends (holidays). In general, on weekdays (blue lines), there is a distinct peak in the morning and evening rush hour, which is more prominent in the morning, i.e., the trips during morning rush hour are more centralized. The evening rush-hour traffic extends from 17:00 to 22:00. The common phenomenon of extra work and long commuting times are the likely causes of this result. At weekends (red lines), a different trend is observed: the line becomes flatter as the commuter peaks diminish, indicating that more people's time becomes available for travel, and leisure trips are the primary trip purpose. The two lines tend toward 0 from 0:00 to 5:00 because subways are closed during this period.



(**a**) (**b**)

Figure 2. Diurnal curves bike sharing trips for accessing rail transit stations: (**a**) Trips on weekdays vs. trips on weekends; (**b**) Trips from origin vs. trips to destination.

Similarly, the probability distribution graphs for the service starting time of Mobike trips from origin and trips to the destination on weekdays are shown separately, as illustrated in Figure 2b. In the morning rush hour, trips from origins (blue line) peak at approximately 7:00. According to the 2017 Beijing Transport Annual Report published by Beijing Transport Institute, the average commute time for Beijing is as high as 62 min. Longer commute times prompts commuters to start earlier. In the first half of the morning rush hour, the right shifts of the red line, compared with the blue line, illustrate that commuters spend approximately 1 h on average on the subway. Similarly, the blue line peaks at around 17:00 in the evening. The right shift of the red line is also detected, indicating that commuters typically spend around 1 h on the rail network after work to reach their home.

4.2. Spatiotemporal Patterns

The spatial layout of a city has a strong influence on movement patterns and social behaviors [32]. This section discusses spatiotemporal patterns and highlights how these patterns reflect the cultural and spatial characteristics of Beijing. Kernel density and cluster techniques were used to investigate how the usage patterns of Mobike as a feeder mode to rail transit are shared among rail transit stations and geographically distributed in the city.

4.2.1. Kernel Density Analysis

The kernel density tool of the ArcGIS software is adopted to calculate the variation distribution density of the trips from origin and trips to destination of Mobikes. Selecting 1 h as an interval, the traffic volumes of the two types of trips around subway stations during weekdays are reflected simultaneously on maps, as illustrated in Figure 3. In these maps, red represents that the number of Mobikes undertaking trips from origin to the rail station is higher than trips from this station to destination, indicating that more bike-sharing demand flows into the rail station than out; green represents the contrary.

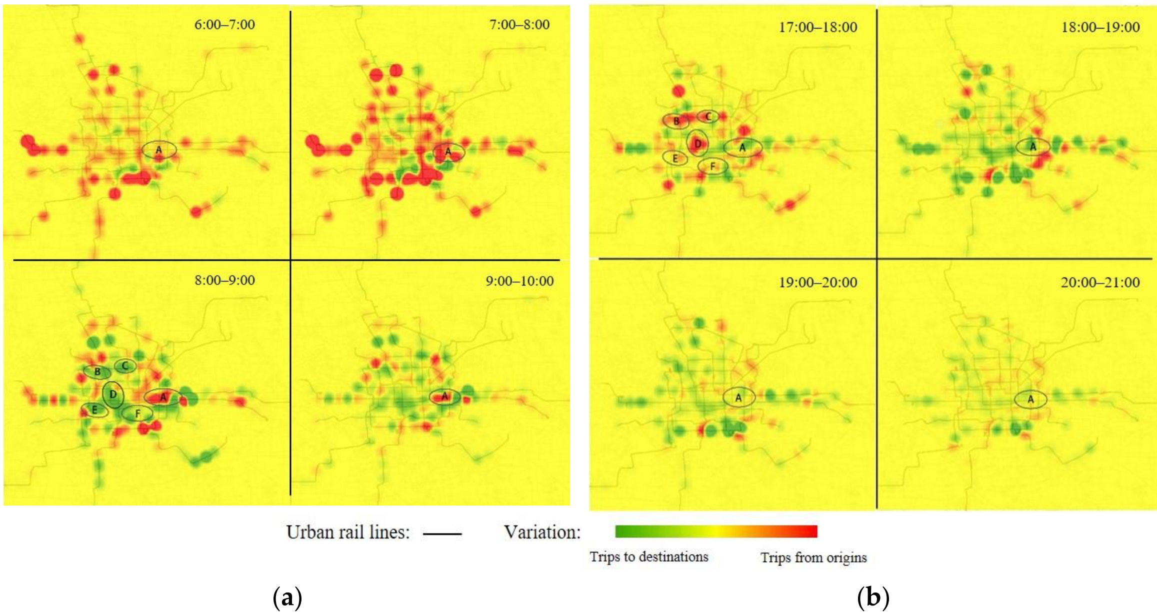


Figure 3. Spatiotemporal activity patterns of the Beijing Mobike during the rush hours on weekdays: (**a**) Morning rush hours; (**b**) Evening rush hours.

Generally, in the morning rush hour (from 6:00 to 10:00), trips from origin (red) increase and then dissipate on the city outskirts; trips to destination (green) gradually increase in the city centers, as illustrated in Figure 3a. From 6:00 to 7:00, trips from origin at subway stations on the outskirts start to increase, and are apparently higher in number than those in the city center. A majority of these areas are located around large-scale residential districts in the urban periphery. A longer commuting distance prompts commuters to depart from their home earlier. After 8:00, trips from origin on the outskirts begin to dissipate, while trips to destination start to increase in the city center. Approximately 1 h after departing from their residences, a large number of commuters arrive at their offices in the city center. After 9:00, this phenomenon gradually dissipates as the majority of the commuters have completed their commuting trips. It is noteworthy that region A in the figure is in a perpetual state of high level of trips from origin. It is the central business district (CBD) of Beijing; therefore, many employment positions, highly intensive mixed land development, and abundant transportation facilities attract millions of people here daily. Meanwhile, the Guomao subway station in the regional center is the busiest transfer station in Beijing with an average passenger flow of 300,000 daily. Bawangfen bus station is 1.8 km from the Guomao subway station. Each day, 350,000 commuters from the eastern suburbs transfer to other modes of transport at this bus station to enter the city in the morning rush hour. Many of them opt to proceed to the Guomao station to change to the subways, and Mobike is a reasonable option for connecting the two. The regions where green is relatively prominent in Figure 3a (from 8:00 to 9:00) include Zhongguancun Science Park (region B), Olympic Common Domain (region C), Financial Street (region D), Lize Financial Business District (region E), and Cultural Circle of the Temple of Heaven (region F). These five regions are major functional zones that accommodate Beijing's cultural, financial, scientific, and technology industries with many jobs. In this regard, many commuters shift to Mobikes here to arrive at work in the morning rush hour.

During evening rush hour, a state contrary to the morning condition appears, as illustrated in Figure 3b. A large number of commuters return to their residences on the outskirts of the city. Compared with the morning rush hour, the integral color of the figure is lighter, indicating that the rush-hour travel lasts longer and is dispersed to a higher degree.

4.2.2. Cluster Analysis

According to the analysis above, the usage patterns of Mobike around different subway stations are different at different times. Hierarchical clustering, one of the most widely used clustering methods, was adopted to classify 277 rail stations with the distribution probabilities of trips from origin and trips to destination on weekdays. The clustering started with a set of clusters, each consisting of one station. A merging criterion, such as single link, complete link, centroid, average or Ward method, should be selected to merge these one-object clusters. Compared with other merging techniques, the average method and Ward method are most commonly used. Considering that Ward's minimum variance method outperforms other hierarchical clustering methods to some extent, we applied the Ward criterion in this study. Common evaluation methods, including the scree test and Kaiser-Harris criterion, were conducted to determine the number of clusters to retain. The scree plot can display the shape of the resulting curve, indicating the maximum number of components to retain, and the Kaiser–Harris criterion suggests the retention of clusters with eigenvalues above 1. Finally, the clusters can be divided into four categories.

The curves of temporal patterns of all categories are drawn and reflected on the map, as illustrated in Figure 4. The abscissa represents time (from 0:00 to 22:00), and the ordinate represents how many trips from origin start (arrive by shared bike at the station) or how many trips to destination finish (depart by shared bike from the station) at this time.

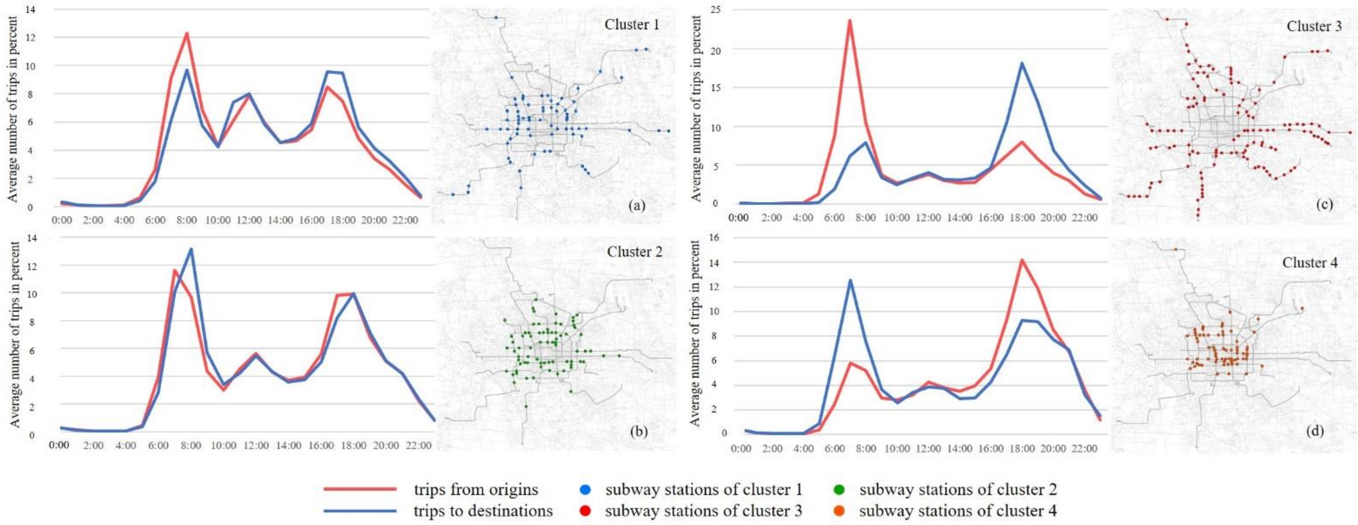


Figure 4. Temporal patterns and geographical distribution of each cluster of subway stations on weekdays: (**a**) Cluster 1 stations; (**b**) Cluster 2 stations; (**c**) Cluster 3 stations; (**d**) Cluster 4 stations.

In general, the curve shapes of all categories exhibit apparent variations.

Cluster 1 exhibits a triple-peak characteristic. The peak time (8:00) in the morning rush is later than the average peak time (7:00, Figure 2b). These stations are mainly distributed on the east and west sides in the vicinity of the central area of the city. The commuters depart later from their residences because of the shorter average commuting distance. Compared with the other three categories, it exhibits the highest proportion of flexible travel; thus, the discrepancy of peak-to-trough is small.

The curve of Cluster 2 is similar to the overall probability density curve (Figure 2b). The curves of the temporal distribution of trips departing from or arriving at the station are generally overlapping; the stations are mainly located in the periphery of the urban core, with a well-proportioned distribution of stations and moderate variation between trips from origin and to destination.

With regard to the stations of Cluster 3, the proportion of trips departing from and arriving at this kind of station during rush hour exhibits significant variation. In the morning rush, the number of Mobike used for departure from origin is significantly higher than that for trips to destination; its peak value is a maximum of 0.24, approximately two times that of the other categories. The situation in the evening rush is opposite to that of the morning rush. This category of station is mainly distributed over the periphery of the city. The longer commuting distance results in earlier departure times in a more concentrated time period. The trip purpose of this category is relatively straightforward—for commuting in most cases. The number of trips departure from origin in the morning rush is apparently higher than the number of trips arriving at destination during the evening rush. On the one hand, the travel in the morning rush is more concentrated; on the other hand, at this category of station, the use of Mobikes is generally counterproductive because during the morning rush, bikes fill the area around the station, leaving no available space for parking, whereas in the evening rush, passengers cannot find a bike to ride.

Cluster 4 presents a contrasting trend to that of Cluster 3. In the morning rush, trips to destination are apparently higher in number than trips from origin. This implies that when few people depart from origin and arrive at such a station for transfer, there have been cases of a number of commuters from other areas of the city arriving here and riding a Mobike toward their destination. This station category is mainly located in the city's central area and concentrated in the six regions (region A–F) mentioned above. Departures of trips from origin during evening hours are significantly higher than arrivals of trips to destination in the morning rush, resulting in a challenge that is the converse of Cluster 3.

4.2.3. Urban Morphology Impact Analysis

Urban morphology affects the travel behavior of residents. The most relevant factor of the trips by cyclist access to rail transit is the characteristics of urban morphology within the bicycle service area around the station. There are differences between bicycle service areas at different stations, and bicycle service areas of adjacent stations may overlap. Therefore, the collections of traffic zones in which the ends of trips accessing rail transit are located are considered bicycle service areas in this study.

Several indicators can describe urban morphology, the most typical of which are the 3D or 5D indicators proposed by Cervero, Kockelman, and Chen et al. [34,35]. Three kinds of indicators are employed in this paper: mixed land-use indicators (including four categories of POI points: residence, office and school, business and public service), built environment indicator (number of intersections), and traffic facilities indicator (number of bus stations).

Analysis of variance (ANOVA) was adopted to determine whether the six indicators above are significantly different between the four major categories of stations. The results indicate that the *p*-values are much lower than 0.001, and the test results of the six indicators are extraordinarily significant, proving significant differences in mixed land-use, built environment, and traffic facilities at various stations.

The ANOVA results indicate that the six indicators are significantly different among the four categories of stations, but this does not mean there is a significant difference between each indicator at any two categories of stations. The Tukey test is a post hoc test that compares the differences between means of values. The value of the Tukey test is given by taking the absolute value of the difference between pairs of means and dividing it by the standard error of the mean as determined by the ANOVA test. Thus, a Tukey HSD analysis was used to determine which indicators of which two stations are significantly different, and the results are shown in Figure 5. Every segment of straight lines represents the distribution of confidence interval at 95% of the difference in two corresponding categories of stations. If the straight line intersects with line $y = 0$, the difference is insignificant; otherwise, the difference is significant. The difference is positive if the straight line is located above line $y = 0$ and negative if below the line $y = 0$.

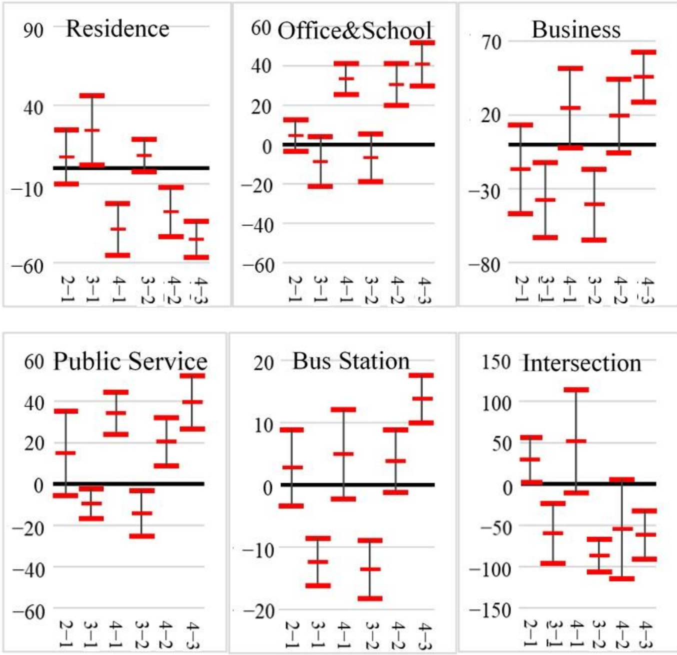


Figure 5. Tukey HSD analysis results of six indicators.

Combining the analysis of the spatial-temporal pattern and the results of ANOVA and Tukey HSD, the following conclusions can be drawn:

1. The POI numbers of residence, office and school have significant effects on Cluster 4 with regard to their bike-sharing operation characteristics. Compared with other categories, the POI numbers for residence are much lower, while the POI numbers for office and school are much larger.
2. The POI numbers of bus stations, intersections and businesses have significant effects on Cluster 3 with regard to their bike-sharing operation characteristics. Compared with other categories, the POI numbers for the three above are much lower. The Cluster 3 stations are mainly located in the periphery of the city where the commercial development, built environment, and traffic facilities are inferior to those at the center of the city.
3. The POI numbers of public service have significant effects on Clusters 3 and 4 with regard to their bike-sharing operation characteristics. Compared with other categories, the POI numbers for the public service of Clusters 4 are much larger. Similarly, as the Cluster 3 stations are mainly located in the suburban areas, its indicator of public service is significantly lower.

According to the above analysis, the stations with uniform land use and relatively strong residential functions of the surrounding area have usage patterns similar to the features shown in Figure 4c. In contrast, the stations with more office and public service functions and fewer residential functions have usage patterns similar to the features shown in Figure 4d. The stations with balanced land use in the surrounding area are close to the usage patterns shown in Figure 4a,b. It can be assumed that the usage patterns of the various stations in Figure 4 are related to the job-to-housing ratio around the subway station.

4.3. Accessing Distance Analysis

The accessing distance for cyclists to rail transit is also influenced by urban morphology, such as station characteristics and the non-motorized transportation environment around the station [36]. This section analyzes the accessing distance of Mobike at four categories of stations to determine the relationships therein. The distance used in the study is the bicycle travel distance recommended by navigation software. Although it is not the actual distance, it approximates the actual situation more precisely than the Euclidean distance. Taking 100 m as the interval in the analysis, the probability density distribution scatter diagrams of accessing distance were generated based on the preliminary assumption that its probability density is a normal distribution. Aided by the MATLAB curve fitting toolbox, the probability density distribution curve of a linear or quadratic normal distribution model was selected to fit the accessing distance of four categories (Figure 5).

The fitting effect is illustrated in Figure 6. SSE and RMSE are approximately 0, and the R-square and adjusted R-square values are approximately 1. Thus, the fitting effect is reasonable.

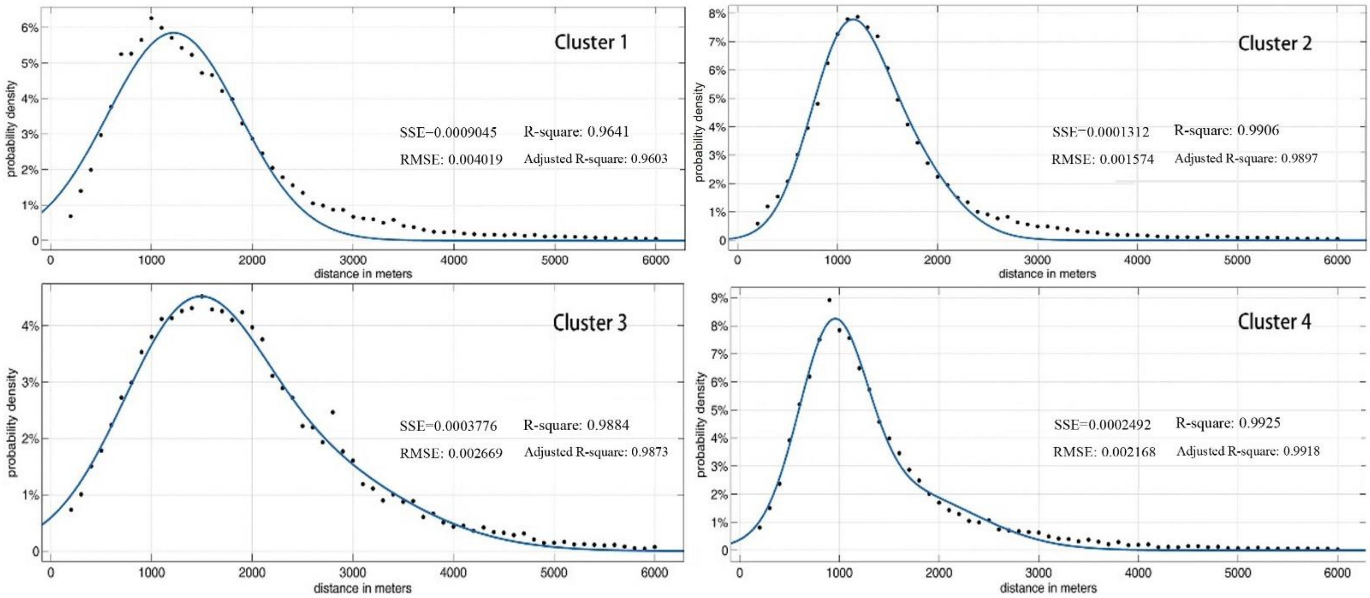


Figure 6. Probability density distribution of accessing distances for FFBS to urban rail transit.

The normal distribution exhibits two symmetrical catastrophe points, of which the right catastrophe point is at 85% cumulative probability, called the 85% quantile. After this quantile, the passenger service rate decreases significantly with an increase in distance. Hence, the distances of all the means of transportation at 85% cumulative probability are deemed as the accessing distance:

$$d_{\text{Cluster1}} = 1874 \text{ m}, \quad d_{\text{Cluster2}} = 1690 \text{ m},$$

$$d_{\text{Cluster3}} = 2460 \text{ m}, \ d_{\text{Cluster4}} = 1467 \text{ m}.$$

According to the fitting results, there are significant variations in the accessing distances of various subway stations. The general rule is that the accessing distance at the urban center is short, whereas it is large at the periphery.

The accessing distance for Cluster 3 stations located in the periphery is significantly larger than those of the other three categories. The land-use mixture and road network density around the stations are low, the distance between the adjacent stations is large, and rail transit is the most convenient means of transport for the residents living in these areas to travel downtown; therefore, travelers are more willing to ride a larger distance to use the rail transit.

Cluster 4 of stations with the shortest accessing distance is located in the urban center. The streets and alleys are densely scattered around the station, the land mixture and public transport coverage are high, and the station spacing is short; therefore, a traveler generally travels a shorter distance to reach the rail transit station, or by selecting other means of transport. Thus, the acceptable critical accessing distance is short. The location of Cluster

1 and Cluster 2, their degree of influence by the urban morphology, and their accessing distances lie between those of Cluster 3 and Cluster 4 stations.

5. Discussion and Conclusions

This study analyzed the operation characteristics of a free-floating bike sharing system as a feeder mode to rail transit in Beijing, considering space and time dimensions. This research was conducted by analyzing GPS data obtained from Mobike and urban morphology impacts. Further, the accessing distance was also analyzed. Several useful discoveries that may pertain to the planning and rebalancing of FFBS in Beijing are as follows:

An obvious morning and evening rush hour in usage patterns of FFBS accessing rail transit on weekdays was observed. From the spatial-temporal dimension, FFBS access to rail transit has an obvious aggregating feature during rush hour. The spatial-temporal features indicate that during the morning rush hour, trips from the origin are first observed at the periphery of the city and then disperse, while trips to destinations are concentrated in the city center. An opposite trend is observed during the evening rush hour.

Imbalanced usage of shared bikes was most likely to occur at stations near major residential areas in the city's suburbs and at stations near the city CBD located in the city center. The opposite trend is found during morning and evening rush hours. Compared to the uniform land use and low job-to-housing ratio around stations in suburban areas, rail transit stations in the city center have relatively high job-to-housing ratios, resulting in a one-way flow of commuting travel during morning and evening rush hours. Thus, it is indicated that for the rebalancing of bike sharing at night, more shared bikes should be placed near the residential areas (Cluster 3) in the suburbs of the city, as well as around the stations (Cluster 4) located in the city center.

The imbalanced usage of shared bikes leads to parking problems. During the morning rush hour, many shared bikes pour into subway stations from residential areas. A similar phenomenon can be seen at the stations in the city center during the evening rush hour. The rapid concentration of shared bikes in a short period, along with disordered parking, indicates a requirement for the implementation and management of parking facilities around subway stations, especially in downtown areas with limited parking spaces. Allocation of sufficient and reasonable parking spaces for shared bikes around the target subway stations mentioned above is recommended, provided that public space resources are used fairly. Further, the assignment of personnel to coordinate and manage the shared bikes around the abovementioned stations during rush hours is also recommended.

The urban morphology and location affect the accessing distance for bike sharing to rail transit. In city suburbs, travelers are more willing to ride longer distances to access rail transit, which indicates that it is reasonable to consider a wider bicycle service area in non-motorized environment planning and bike sharing planning around the stations. Simultaneously, creating attractive public transport and bicycle-friendly environments, and integrating bike sharing and high-quality public transport are critical to the new housing and office developments, which also makes sense to alleviate parking problems.

This study analyzed the operation characteristics of Mobike as a feeder mode to rail transit in Beijing, which has significance as a reference for other cities integrating bike sharing and rail transit systems and solving the problem of the first or last mile. However, due to the limited access to data, this study analyzes only Mobike data, without consideration of the service conditions of other brands (such as Ofo, Bluegogo, etc.). In addition, the deviation of the GPS data of FFBS may impact the accuracy of analysis results to some extent. Although Mobike applies both GPS-based and base station-based positioning methods to improve the positioning accuracy, deviations are still unavoidable, especially when shared bikes are surrounded by buildings that interfere with signals. These deviations may lead to inaccurate data on bike-sharing trip OD locations. Due to the limitation of the GPS dataset, this study has not been able to provide an in-depth analysis of influence of these deviations, which is a limitation of this paper. In addition, other factors affecting the success of FFBS access to rail transit may include season, weather, and policy adjustment, which should be further examined in future research.

Author Contributions: Conceptualization, X.G.; Data curation, J.L.; Formal analysis, J.L.; Methodology, J.L.; Writing—original draft, J.L.; Writing—review and editing, J.L. and X.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Social Science Foundation of Jiangsu Province under Grant 18WTA009.

Data Availability Statement: Upon request, the data can be obtained from the authors.

Acknowledgments: Additional thanks to Fang Lv and Xiaotian Zhang for insightful comments and suggestions on the interpretation of the whole paper.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Zhang, M.Z.; He, S.J.; Zhao, P.J. Revisiting inequalities in the commuting burden: Institutional constraints and job-housing relationships in Beijing. *J. Transp. Geogr.* **2018**, *71*, 58–71. [CrossRef]
2. Shen, Q.; Sanchez, T.W. Residential location, transportation, and welfare-to-work in the United States: A case study of Milwaukee. *Hous. Policy Debate* **2005**, *16*, 393–431. [CrossRef]
3. Yan, D.M.; Guo, J.H.; Liu, Z.; Huang, W. A Novel Hybrid Evaluation Method for Transfer Efficiency Assessment between Rail Transit and Public Bicycles. *Promet-Traffic Transp.* **2020**, *32*, 279–289. [CrossRef]
4. Fan, Y.L.; Guthrie, A.; Levinson, D. Waiting time perceptions at transit stops and stations: Effects of basic amenities, gender, and security. *Transp. Res. A-Pol.* **2016**, *88*, 251–264. [CrossRef]
5. Griffin, G.P.; Sener, I.N. Planning for Bike Share Connectivity to Rail Transit. *J. Public Transp.* **2016**, *19*, 1–22. [CrossRef]
6. Krauss, K.; Krail, M.; Axhausen, K.W. What drives the utility of shared transport services for urban travellers? A stated preference survey in German cities. *Travel. Behav. Soc.* **2022**, *26*, 206–220. [CrossRef]
7. Pal, A.; Zhang, Y. Free-floating bike sharing: Solving real-life large-scale static rebalancing problems. *Transp. Res. C-Emer.* **2017**, *80*, 92–116. [CrossRef]
8. Glotz-Richter, M. Reclaim street space!—Exploit the European potential of car sharing. *Transp. Res. Proc.* **2016**, *14*, 1296–1304. [CrossRef]
9. Cheng, L.; Wang, K.L.; De Vos, J.; Huang, J.; Witlox, F. Exploring non-linear built environment effects on the integration of free-floating bike-share and urban rail transport: A quantile regression approach. *Transp. Res. A-Pol.* **2022**, *162*, 175–187. [CrossRef]
10. Xin, R.; Ai, T.H.; Ding, L.F.; Zhu, R.X.; Meng, L.Q. Impact of the COVID-19 pandemic on urban human mobility-A multiscale geospatial network analysis using New York bike-sharing data. *Cities* **2022**, *126*, 103677. [CrossRef]
11. Jiao, J.F.; Lee, H.K.; Choi, S.J. Impacts of COVID-19 on bike-sharing usages in Seoul, South Korea. *Cities* **2022**, *130*, 103849. [CrossRef] [PubMed]
12. Song, J.; Zhang, L.Y.; Qin, Z.; Ramli, M.A. Spatiotemporal evolving patterns of bike-share mobility networks and their associations with land-use conditions before and after the COVID-19 outbreak. *Phys. A* **2022**, *592*, 126819. [CrossRef]
13. Teixeira, J.F.; Silva, C.; Sa, F.M.E. The motivations for using bike sharing during the COVID-19 pandemic: Insights from Lisbon. *Transp. Res. F-Traf.* **2021**, *82*, 378–399. [CrossRef] [PubMed]
14. Teixeira, J.F.; Silva, C.; Sa, F.M.E. The role of bike sharing during the coronavirus pandemic: An analysis of the mobility patterns and perceptions of Lisbon's GIRA users. *Transp. Res. A-Pol.* **2022**, *159*, 17–34. [CrossRef]
15. Hu, S.H.; Xiong, C.F.; Liu, Z.Q.; Zhang, L. Examining spatiotemporal changing patterns of bike-sharing usage during COVID-19 pandemic. *J. Transp. Geogr.* **2021**, *91*, 102997. [CrossRef] [PubMed]
16. Ji, Y.J.; Fan, Y.L.; Ermagun, A.; Cao, X.N.; Wang, W.; Das, K. Public bicycle as a feeder mode to rail transit in China: The role of gender, age, income, trip purpose, and bicycle theft experience. *Int. J. Sustain. Transp.* **2017**, *11*, 308–317. [CrossRef]
17. Chen, D.W. Free-floating bike-sharing green relocation problem considering greenhouse gas emissions. *Transp. Saf. Environ.* **2021**, *3*, 132–151. [CrossRef]
18. Li, X.F.; Zhang, Y.; Du, M.Y.; Yang, J.Z. Social Factors Influencing the Choice of Bicycle: Difference Analysis among Private Bike, Public Bike Sharing and Free-Floating Bike Sharing in Kunming, China. *KSCE J. Civ. Eng.* **2019**, *23*, 2339–2348. [CrossRef]
19. Zhuang, C.G.; Li, S.Y.; Tan, Z.Z.; Feng, G.; Wu, Z.F. Nonlinear and threshold effects of traffic condition and built environment on dockless bike sharing at street level. *J. Transp. Geogr.* **2022**, *102*, 103375.
20. Wang, Y.T.; Sun, S.H. Does large scale free-floating bike sharing really improve the sustainability of urban transportation? Empirical evidence from Beijing. *Sustain. Cities Soc.* **2022**, *76*, 103533. [CrossRef]
21. Xing, Y.Y.; Wang, K.; Lu, J.J. Exploring travel patterns and trip purposes of dockless bike-sharing by analyzing massive bike-sharing data in Shanghai, China. *J. Transp. Geogr.* **2020**, *87*, 102787. [CrossRef]

22. Schuijbroek, J.; Hampshire, R.C.; van Hoeve, W.J. Inventory rebalancing and vehicle routing in bike sharing systems. *Eur. J. Oper. Res.* **2017**, *257*, 992–1004. [CrossRef]
23. Shui, C.S.; Szeto, W.Y. Dynamic green bike repositioning problem—A hybrid rolling horizon artificial bee colony algorithm approach. *Transp. Res. Part D Transp. Environ.* **2018**, *60*, 119–136. [CrossRef]
24. Liu, Y.; Szeto, W.Y.; Ho, S.C. A static free-floating bike repositioning problem with multiple heterogeneous vehicles, multiple depots, and multiple visits. *Transp. Res. C-Emer.* **2018**, *92*, 208–242. [CrossRef]
25. Caggiani, L.; Camporeale, R.; Ottomanelli, M.; Szeto, W.Y. A modeling framework for the dynamic management of free-floating bike-sharing systems. *Transp. Res. C-Emer.* **2018**, *87*, 159–182. [CrossRef]
26. Fishman, E. Bikeshare: A Review of Recent Literature. *Transp. Rev.* **2016**, *36*, 92–113. [CrossRef]
27. Feng, Y.L.; Affonso, R.C.; Zolghadri, M. Analysis of bike sharing system by clustering: The Velib' case. *IFAC Pap.* **2017**, *50*, 12422–12427. [CrossRef]
28. Martin, E.W.; Shaheen, S.A. Evaluating public transit modal shift dynamics in response to bikesharing: A tale of two US cities. *J. Transp. Geogr.* **2014**, *41*, 315–324. [CrossRef]
29. Faghih-Imani, A.; Anowar, S.; Miller, E.J.; Eluru, N. Hail a cab or ride a bike? A travel time comparison of taxi and bicycle-sharing systems in New York City. *Transp. Res. A-Pol.* **2017**, *101*, 11–21. [CrossRef]
30. Ma, T.; Liu, C.; Erdogan, S. Bicycle Sharing and Public Transit Does Capital Bikeshare Affect Metrorail Ridership in Washington, DC? *Transp. Res. Rec.* **2015**, *2534*, 1–9. [CrossRef]
31. Flamm, B.J. Determinants of Bicycle-On-Bus Boardings: A Case Study of the Greater Cleveland RTA. *J. Public Transp.* **2013**, *16*, 67–84. [CrossRef]
32. Froehlich, J.; Neumann, J.; Oliver, N. Sensing and Predicting the Pulse of the City through Shared Bicycling. In Proceedings of the 1st International Joint Conference on Artificial Intelligence (Ijcai-09), Vienna, Austria, 23–29 July 2022; pp. 1420–1426.
33. Braun, L.M.; Barajas, J.M.; Lee, B.; Martin, R. Walking the Last Mile: Barriers and Solutions to Suburban Transit Access. *Transp. Res. Rec.* **2022**. [CrossRef]
34. Cervero, R.; Kockelman, K. Travel demand and the 3Ds: Density, diversity, and design. *Transp. Res. Part D Transp. Environ.* **1997**, *2*, 199–219. [CrossRef]
35. Chen, Z.Y.; van Lierop, D.; Ettema, D. Travel satisfaction with dockless bike-sharing: Trip stages, attitudes and the built environment. *Transp. Res. Part D Transp. Environ.* **2022**, *106*, 103280. [CrossRef]
36. Liu, X.H.; Fan, J.; Li, Y.; Shao, X.; Lai, Z.L. Analysis of integrated uses of dockless bike sharing and ridesourcing with metros: A case study of Shanghai, China. *Sustain. Cities Soc.* **2022**, *82*, 103918. [CrossRef]