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Examining factors associated with bike-and-ride (BnR) activities around metro stations in large-scale dockless bikesharing systems

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ABSTRACT

Dockless bikesharing (DBS) has been considered as a solution to the first and last mile problem of metro connectivity. Leveraging data covering all DBS programs in Shanghai, China, this study evaluated bike-and-ride (BnR) activities in DBS-metro systems via four metrics: BnR trip count, BnR rate, shared-bike utilization rate, and catchment size (85th percentile transfer distance). A set of generalized additive models considering marginal nonlinear interactions was fitted to examine associations between the four metrics and external environment, including land use, socio-demographics, roadway designs, transportation facilities, metro station features, and DBS operator features. Different buffer sizes measured by network distance were tested to check model robustness and find optimal buffers. Results showed that: 1) metro stations near the city center exhibited greater BnR trip count, higher BnR rate, lower shared-bike utilization rate, and smaller catchment size; 2) proportion of public and residential land suggested positive relationships with BnR trip count but lose their significances after offsetting metro ridership; 3) numbers of colleges, shopping malls, and carsharing stations presented positive relationships with both BnR trip count and BnR rate; 4) land use mix was significantly positively associated with BnR trip count only when buffer size was larger than 1.5 km; 5) regions with higher population density went from less BnR activities in the city center to more BnR activities in the suburbs; 6) Large DBS operators outperformed small ones in BnR trip count but not in bike utilization rate. Taken together, this study uncovers a spatially disproportionate and supply-demand unbalanced distribution of DBS resources, which could attenuate the efficiency and attractiveness of using DBS to BnR. DBS operators and local governments should evaluate DBS systems from multiple perspectives to avoid an oversupplied and over-competing market.

1. Introduction

Since 2016, cycling has regained popularity worldwide, aided in part by the growing prevalence of dockless bikesharing (DBS) (Shaheen and Cohen, 2019). The propagation of DBS has led to unprecedented growth in scale, boosting the number of dockless shared bikes to more than 23 million and spreading to over 200 cities within one year (Gu et al., 2019; Han, 2020). The renaissance of DBS is due to its considerable convenience and high flexibility. When dockless shared bikes are adequately provided on streets, no constraint is placed on the borrow and return of bikes. Anyone with an app can unlock a shared bike and ride it wherever they want, unlike in docked bikesharing systems where bikes have to be returned to fixed stations. Users also no longer need to worry about empty stations at departure or full stations upon arrival. In addition, in contrast to traditional public bike systems mainly offering long-term packages, DBS allows users to pay by trip with lower price, which is more attractive to users with short and spontaneous trips.

The higher flexibility and efficiency of DBS contribute to tight integration with public transit in China (Guo et al., 2021). One recent report stated that in Beijing, China, approximately 81% and 44% of shared bikes were found to be active within 300 m of bus stops and 500 m of metro stations (Chen et al., 2020). Another report based on Meituan bike (the original Mobike) stated that in cities with total metro lines longer than 300 km, over 35% of DBS trips were found to be started or ended

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within 100 m of metro stations (COUPO, 2021). Such a tight connection between shared bikes and public transit is driven by both demand and supply. On the demand side, metro systems generate substantial passenger flow, providing sufficient cycling demand from or to metro stations. On the supply side, DBS operators endeavor to locate their bikes nearby metro stations to maximize their profits and dominate the market. However, unintended consequences emerged due to the failure in maintaining supply-demand balance (Shaheen and Cohen, 2019; Shaheen et al., 2020; Tu et al., 2019). Driven by the aggressive capital expansion, DBS operators dispatched most of their shared bikes to popular metro stations, for example, metro stations located near the city center, without considering the actual demand or the capacity of public spaces. As a result, oversaturated DBS became a ubiquitous issue near the city center (Gu et al., 2019; Tu et al., 2019). Haphazardly parked shared bikes clogged sidewalks and compressed public spaces, which can be seen as a violation of non-shared-bike users' rights. On the contrary, metro stations located in the suburb were substantially neglected by DBS operators (Li et al., 2020; Li et al., 2021; Xing et al., 2020). Suburban residents who suffer from underserved transport services are in urgent need of a complementary option to fill their mobility gap. However, undersupplied DBS resources make them difficult to find available shared bikes, exacerbating the inequality in transport accessibility between urban and suburban areas.

The key solution to the above problem is to comprehensively understand BnR activities in DBS-metro systems, accurately estimate BnR demand of riding shared bikes, and appropriately allocate geographically differentiated shared bike quotas. Three research questions are proposed to achieve those objectives:

1) How to distinguish BnR trips from raw DBS trips when cyclers' trip chains information is unavailable?
2) How to evaluate BnR activities from different participants' perspectives such as DBS operators, metro authorities, and DBS users?
3) What factors are associated with different BnR metrics, and do estimated relationships hold robust under different buffer sizes?

To answer the above questions, this study took metro stations in Shanghai, China as the analytical anchors to explore BnR activities in DBS systems. Building on previous work related to bikesharing usage, this study contributes to the field from the following aspects:

1) Large-scale, population-level trip data covering all DBS programs in Shanghai was analyzed. 2) A spatial density-based method was proposed to identify BnR trips based on their network proximity to metro stations. 3) Four metrics were calculated to evaluate BnR performance from different perspectives, including BnR trip count, BnR rate, shared-bike utilization rate, and catchment size. 4) A set of generalized additive models was fitted to examine relationships between the four metrics and various potential determinants, with the consideration of marginal nonlinear interactions and spatial dependence. 5) Relationships among different shared mobility services were examined, including relationships with carsharing and interrelationships among bikesharing operators. 6) The optimal buffer size to calculate surrounding environments was found for each BnR metric based on the model bootstrapping goodness-of-fit. Results help evaluate BnR performance, estimate BnR demand, and promote the efficiency and attractiveness of BnR in DSB-metro systems. Experience gained from Shanghai also offers a useful lesson for other cities worldwide that are experiencing similar DBS renaissances.

2. Literature review

Because DBS is relatively new and related data are not widely opened to the public, studies investigating DBS are sparser compared with docked bikesharing. Yet, prior studies on docked bikesharing are still informative since docked and dockless bikesharing are broadly similar in the services they provided and the roles they played in the whole transportation system, despite there exist some differences regarding rental rules and price plans (Chen et al., 2020; Gu et al., 2019). The following literature review includes studies in both docked and dockless bikesharing.

2.1. Factors associated with bikesharing usage

Various studies on bikesharing usage have already been conducted. Among them, dependent variables, i.e. the bikesharing usage, are aggregated in different spatial units (bikesharing stations; metro station catchment areas, TAZs, census block groups, or census tracts for DBS), and separated by temporal features (weekdays versus weekends, peak hours versus non-peak hours), user groups (younger versus elder, male versus female, low-income versus medium/high-income, member versus casual) and trip characteristics (long distance versus short distance) (Caspi and Noland, 2019; Hu et al., 2021b; Noland et al., 2016). Independent variables can be summarized as land use, socio-economics, socio-demographics, roadway designs, transportation facilities, cycling infrastructures, and weather conditions (Noland et al., 2016, 2019; Sun et al., 2018).

Most prior findings are consistent and intuitive. Areas near the city center, with higher population density, higher income, denser cycling facilities, greater transit proximity, higher land use mix, and better weather conditions, are more likely to generate more cycling demand, either in docked (Hu et al., 2021b; Noland et al., 2016, 2019; Sun et al., 2018) or dockless bikesharing systems (Guo and He, 2020; Jing et al., 2021; Shen et al., 2018). Colleges, parks, shopping centers, green parks, and residential areas are widely considered as the top popular land-use type attracting bikesharing usage (Guo and He, 2020; Mattson and Godavarthy, 2017; Schimohr and Scheiner, 2021). On the contrary, unfriendly cycling environments, such as high speed limit, poor streetlight, low green-space coverage, steep terrain, damaged road surfaces, and sparser bikesharing services all contribute to low bikesharing usage (Jing et al., 2021; Sun et al., 2018).

2.2. Relationship between bikesharing and transit

The relationship between bikesharing and transit has gained wide discussion over recent years (Kong et al., 2020; Martin and Shaheen, 2014). Whether the relationship is complementary or substitutive is inconclusive. A variety of regressions between bikesharing usage and transit services fitted in prior studies revealed a positive relationship, which can be seen as the evidence for a complementary relationship (Noland et al., 2016, 2019; Shen et al., 2018). However, some before-and-after analyses also found a reduction in transit ridership after the introduction of bikesharing, which supports a substitutive relationship (Schimohr and Scheiner, 2021). One recent study summarized the relationship between bikesharing and transit into substitution, integration, and complementation, and stated the relationship is decided by who takes the trip and when (Kong et al., 2020). Some studies (Ji et al., 2018) further examined the intertwined relationships among bikesharing, bus, and metro and found that the higher density of bus services near a subway station, the lower the combined usage of bikesharing and metro, which may be explained by the competition between bus and bikesharing in accessing metro.

The integration usage of bikesharing and transit, i.e. the BnR activity, has also gained some explorations in both docked (Ji et al., 2017; Ji et al., 2018; Lin et al., 2018; Ma et al., 2018a; Ma et al., 2018b) and dockless bikesharing systems (Guo and He, 2020, 2021a; Li et al., 2021). Metro stations with larger passenger ridership, located in regions near the city center, with higher land-use mix, denser cycleways, more bikesharing stations, more entertainment and residential lands are more likely to generate more BnR trips (Guo and He, 2020, 2021a, 2021b; Guo et al., 2021; Ji et al., 2017; Ji et al., 2018; Li et al., 2021; Lin et al., 2018; Ma et al., 2018a; Ma et al., 2018b). Some researchers compared the docked and dockless bikesharing usage at metro stations and stated the two types of bikesharing are highly similar except the docked bikesharing may be more frequently used for commuting (Chen et al., 2021). Moreover, some studies focused on the relationship between built environment and catchment area (or transfer distance) instead of bikesharing usage (Li et al., 2021; Ma et al., 2018a). Their results documented a negative correlation between catchment area and bikesharing usage.

2.3. Methods of modeling bikesharing usage

To narrow down the review scope, here we only focused on statistical methods. Traditional ordinary least squares (OLS) regression is not appropriate given the over-dispersion and non-normal nature of bikesharing usage (Noland et al., 2016). To address this problem, the negative binomial regression and the multilevel mixed model are widely used (Guo and He, 2021a; Hu et al., 2021b; Noland et al., 2016). In addition, spatiotemporal autocorrelation is another common issue when dealing with cross-sectional spatial data or conducting longitudinal analysis. To address that, several mixed-structure models combined with the autoregressive moving average (ARMA) (Hu et al., 2021b) or spatial additive terms are proposed (Caspi and Noland, 2019; Hu et al., 2018; Noland et al., 2016; Sun et al., 2018). Spatial regressions such as spatial error model and spatial lag model have also been employed to address spatial autocorrelation (Faghih-Imani and Eluru, 2016b; Ma et al., 2018a). Geographically weighted regression is another popular option to address spatial heterogeneity by allowing estimations to vary spatially (Li et al., 2021). Recently, the endogeneity bias regarding station capacity and bikesharing usage, aka the installation process biases, has drawn some attention (Faghih-Imani and Eluru, 2016a) and multi-level joint frameworks like structural equation modeling are proposed (Faghih-Imani and Eluru, 2016a; Jing et al., 2021). Besides the modeling approach, another issue is regarding the modifiable area unit problem (MAUP), which postulates that different buffer sizes used to aggregate the variables may lead to different modeling results (Gao et al., 2021; Zhang et al., 2019). However, currently few studies have considered this when modeling bikesharing usage. Experienced-based rules instead of evidence-based methods are mainly used to determine the aggregation unit.

Taken together, although a range of previous studies has examined bikesharing usage near metro stations or bus stops, several research gaps still exist and deserve further research. First, most previous studies only examined one BnR metric, for example, BnR trip count or transfer distance, while a comprehensive evaluation framework from different perspectives and a joint comparison among different metrics are vacant. Second, most key distance parameters, such as the distance to identify BnR trips and the buffer size to calculate influential factors, are generally experience-based instead of evidence-based. A network-based spatial analysis to determine these parameters as well as to check model robustness is needed. Third, limited studies have considered the relationships among different shared mobility services, such as the potential competition among bikesharing operators and the cooperation with carsharing services. Our study aims to fill these gaps by considering a set of BnR metrics, incorporating multi-source shared mobility information, and finding optimal parameters based on model goodness-of-fit.

3. Research design

3.1. Study area

This study took Shanghai as a case area, which is the largest financial hub in China, owning 24.23 million residents and covering an area of 6340 km^2 by 2018. Shanghai is well-equipped with cycling facilities and maintains a high cycling mode share (29.4% from the 2015 Shanghai 5th Comprehensive Transportation Survey (2015 SCTS)). Shanghai is also one of the first Chinese cities to operate bikesharing programs. As early as 2009, docked bikesharing was introduced by the Shanghai government to alleviate mobility issues but failed to thrive due to the station's limited access and spontaneity (Gu et al., 2019). In 2015, a DBS program named Mobike was founded, capitalizing on the shortcoming of docked bikesharing, and quickly making Shanghai the world's largest DBS city by 2016 (Han, 2020; Xing et al., 2020). Due to the huge market, the strong government support, and the aggressive capital investment, dozens of DBS programs eagerly entered the market, pouring millions of shared bikes into Shanghai. By 2018, the total number of dockless shared bikes in Shanghai is over 1.3 million, generating over 2 million rides per day.

DBS has been frequently referred to as a solution to the first and last mile problem of transit connectivity. Shanghai also has a well-served public transit system. By 2017, Shanghai had 1461 routes with 16,700 buses, 17 rail lines, and 673 km in length. Shanghai also maintains a high mode share of transit (21.6% from 2015 SCTS), which is mainly due to the high dependence of commuting trips on public transit, especially the metro system.

With the prevalence of DBS in Shanghai, a large proportion of cycling trips are generated by DBS in an increasing trend. From the 2018 Shanghai Comprehensive Annual Transportation Report, in 2018, the daily average number of cycling trips, including shared-bike trips and private-bike trips, was 5.3 million, among which DBS accounted for ~40%. Such a proportion keeps growing since the number of private bikes has decreased sharply over recent decades in Shanghai. By 2015, the number of daily active private bikes was 1.55 million, decreasing by ~70% compared with that of 2009 (2015 SCTS). Under such circumstances, we believe Shanghai is a representative case to explore the travel behaviors of using DBS as a feeder mode of the metro, to understand underlying determinants, and to deepen insights on how to promote DBS attractiveness in connecting to the metro system.

3.2. Data source

The quick expansion of DBS has posed challenges for local governments on how to manage the massive shared-bike fleet (Gu et al., 2019; Han, 2020; Tu et al., 2019). To better manage, the Shanghai government requires all DBS operators to submit their transaction data to the Shanghai Transportation Information Center, which is the organization our data obtained from. In total, one-week data excluding weekends from May 7th to May 11th, 2018, was archived, covering 8 operators across the entire Shanghai city. Among them, the top four operators regarding the number of trips were Mobike (50.16%), Ofo (34.40%), Xiangqi Bike (8.37%), and 99 Bike (7.04%). The average daytime temperature of the studied week ranged from 21 °C to 29 °C and weather conditions were either sunny or cloudy, which were fairly suitable for cycling. For each DBS trip, the reported information included bike ID, lock status, service provider, timestamps, and geographical coordinates of origins and destinations. Besides DBS trip records, another dataset was from the Shanghai Metro Bureau, containing hourly passengers boarding and alighting at each metro station.

To the best of the authors' knowledge, in contrast to prior studies only analyzed one bikesharing program (Li et al., 2021; Xing et al., 2020), this study is among the first to analyze trips from all DBS programs in Shanghai. In 2018, no DBS program has monopolized the DBS market in Shanghai. Also, different DBS operators may allocate region-specific numbers of shared bikes based on their own market strategies. Hence, using data from one DBS program may incur sampling bias caused by nonrandom and operator-specific allocation processes. The population-level DBS trips employed in this study help eliminate such sampling bias and make findings more reliable. Another advantage of studying all DBS operators is that we can explore the underlying interrelationship among different DBS providers, which can be achieved by incorporating the market share of each DBS provider and other operator-specific features in the model.

Several filters were applied to the raw DBS trip roster before further data processing. First, to match up to the Shanghai metro's operation hours (5:25 to 23:00), DBS trips were tailored into the same period. Second, as bikesharing operators always employ staff members to reallocate shared bikes to alleviate systematic imbalance, the reallocation trips should be removed. The rule to identify reallocation trips is to select the trips with "Lock Status" as True but with different origins and destinations. A trip generated by users cannot be moved and completed when the bike is locked. However, in the reallocation process, those trips are common since bikes are generally locked and moved by trucks in batches. Third, there existed some outliers with too short or long travel time. Based on prior studies, trips with durations less than 1 min or greater than 360 min were identified as outliers and were dropped (Hu et al., 2021b). We did not apply filters on trip distance or speed since we did not have the real trip distance measured by trajectory. For example, a round trip with a very close origin and destination although has a near-zero Euclidean distance may have a long riding distance and should not be excluded as the outlier. Last, considering DBS programs did not cover all regions in Shanghai, we removed the metro stations outside the DBS operation areas.

The spatial distribution of shared bike pickup density and metro passengers boarding are mapped in Fig. 1. One distinguishable pattern is subdistricts with higher density of DBS pickups are mainly concentrated in the city center. This is mainly due to the unequal distribution of DBS resources from the supply side. To maximize profits, shared bikes were heavily oversupplied in urban areas but inadequately provided in suburban areas. The metro system, on the other hand, although also exhibits greater passenger boarding near the city center, remains some stations located in the suburb presenting higher passenger flow.

It is worth mentioning that DBS has experienced a substantial rise and fall over recent years (Gu et al., 2019). In late 2018, Ofo declared serious cash flow issues and largely halted its expansion, followed by waves of bankruptcies of other smaller players. In 2019, Mobike was fully taken over by another company and changed its name to Meituan bike. Meanwhile, other programs such as Hello Bike gradually grew up and replaced Ofo as the top two largest DBS programs in China. As we did not have DBS trip records after 2018, results drawn from this study may vary as the DBS programs progressed.

3.3. Methodology

The methodology framework is presented in Fig. 2. First, a spatial density-based method was used to determine the optimal area to distinguish BnR trips from raw DBS trips based on their network proximity to metro stations (Section 3.3.1). Then, based on the selected BnR trips, four metrics, including BnR trip count, shared-bike utilization rate, catchment size (the 85th percentile transfer distance), and BnR rate, were calculated to comprehensively assess BnR performance (Section 3.3.2). With the four metrics as dependent variables, and incorporating various surrounding potential determinants as independent variables, a set of generalized additive models (GAMs) was fitted to examine underlying associations (Section 3.3.3). A loop was built on top of GAMs by going through different buffer sizes when calculating independent variables to find the optimum via the bootstrapping model goodness-of-fit (Section 3.3.4).

3.3.1. Definition of BnR trips

To examine BnR using DBS, the first step was to extract BnR trips from the raw DBS trip dataset. As we did not know the detailed trip chain of each DBS rider, we could only select BnR trips based on their network

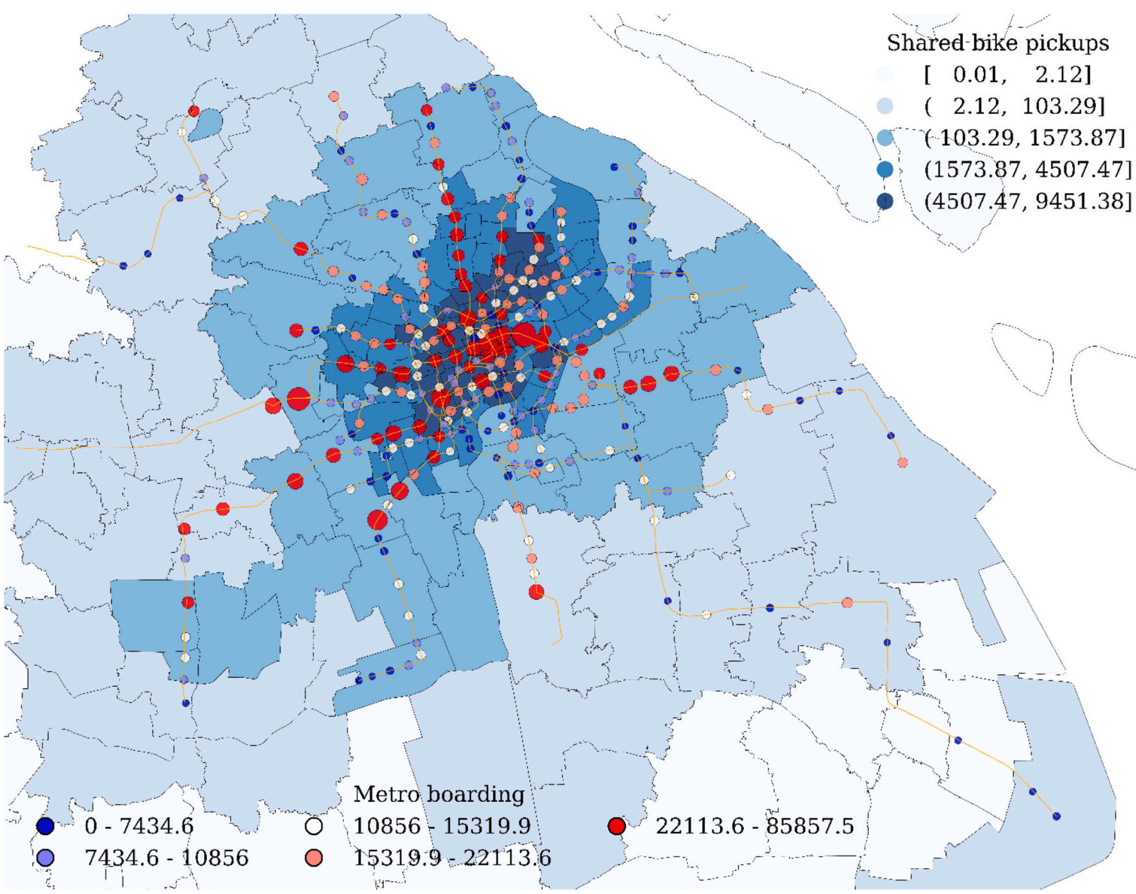


Fig. 1. Spatial distribution of shared bike pickups (subdistrict-level) and metro boarding (station-level). Shared bike pickups represent subdistrict-level density of daily (exclude midnight) average DBS trip's origins (unit: counts/km^2). Metro boardings represent metro station-level daily average number of passengers boarding. Only areas with metro lines covered are shown.

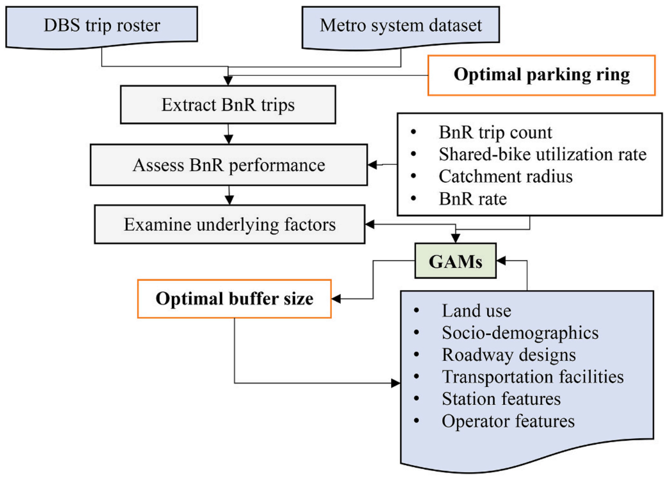


Fig. 2. Methodology framework.

proximity to metro stations. Similar to previous studies (Li et al., 2021; Wu et al., 2021), we defined BnR trips as those with origins or destinations within a certain distance to the metro station, which delineates the most plausible "parking ring" around the metro station. A large parking ring may include noisy trips while a small ring may miss some real BnR trips. Thus, we proposed a spatial network-density-based method to determine the best size of the parking ring. The underlying assumption is that the metro station can affect the nearby density of DBS trips via the production or attraction of BnR trips. Thus, we assumed DBS trip density increases at first with the increase of the parking ring but decays as the parking ring gets larger.

Methodologically, for each metro station, we successively increased the size of the parking ring and calculated the partial increase of DBS trip density. To better represent the real cycling scenario, the size of the parking ring is measured by the network distance, and its boundary is obtained by the concave hull of all reachable nodes. We then standardized it by dividing the partial change of trip density at the maximal parking ring. The partial change of DBS trip density and its standardization were calculated as Eqs. (1–2). It is easy to prove that $\lim_{\Delta \to 0} D_{r,k} \to \partial D / \partial r$, i.e. $D_{r,\,k}$ is the approximate partial derivative of DBS trip density on the size of the parking ring.

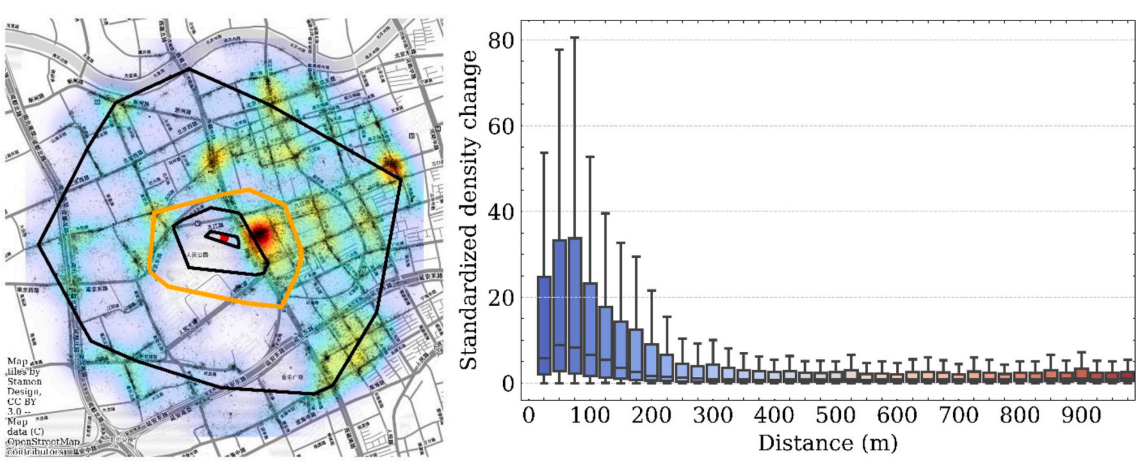
$$D_{r,k} = \frac{\sum_{i=1}^{n_k} I\left(\min\left(d_{O_i,k}, d_{D_i,k}\right). < r + \Delta\right) - \sum_{i=1}^{n_k} I\left(\min\left(d_{O_i,k}, d_{D_i,k}\right). < r\right)}{\pi\left((r+\Delta)^2 - r^2\right)} \quad (1)$$

$$f(r) = \widetilde{D}_{r,k} = D_{r,k} / D_{R,k}, r = \Delta, 2\Delta, \ldots, R \quad (2)$$

where $D_{r,\,k}$ is the partial trip density change at metro station k with the size of parking ring equal to r; $\widetilde{D}_{r,k}$ is its standardization; Δ is the searching step size, here we set it as 25 m; n_k is the number of trips within the maximal parking ring with a size of R, here we set R as 1000 m; $d_{Oi,\,k}$ is the network distance from the origin of trip i to the metro station k; $d_{Di,\,k}$ is the network distance from the destination of trip i to the metro station k; $I(.)$ is the indicator function.

The illustration of different parking rings to define BnR trips and the relationship of $f(r) = \widetilde{D}_{r,k}$ are depicted in Fig. 3. An increase-decrease pattern can be observed in Fig. 3 (b), indicating $f(r)$ successfully corroborated our assumption. The optimal size of parking rings to extract BnR trips was then set as 500 m, which is the value when $f(r)$ converges in terms of both mean and variance. Such value is also confirmed by Fig. 3 (a). The parking ring with a size of 500 m (orange circle) well covers hotspots near metro station entrances, without including trips with farther origins or destinations. Note that 500 m is in line with another similar study based on the Shanghai DBS system (Li et al., 2021) but is larger than some other studies using 100 m as a threshold (Guo and He, 2020; Guo et al., 2021). The main reasons are because their parking rings are in Euclidean distance and are based on metro entrances. In our cases, we don't have geo-information of metro entrances, and thus each metro station is represented by a single centroid point. Therefore, using a 100 m parking ring cannot cover most nearby trips since the metro station itself has a floor area (See Fig. 3 (a) for an illustration).

One caveat here is that even using the spatial density-based algorithm, we still cannot ensure that all trips located inside the parking rings all belong to BnR trips, considering there may be commercial or office-related activities occurring near metro stations, especially in the main urban area. A more accurate method to obtain BnR trips is to collect trip chains of riders based on surveys or experiments equipped with geo-tracking technologies. However, considering the high cost of those data collection processes, metrics calculated in our study can serve as a proxy of BnR activities when the trip chain information is not



(a) (b)

Fig. 3. Illustration of different parking rings (a) and Boxplot of DBS trip density changes across different parking rings (b). Panel (a) depicts the People's Square metro station. Black spots are the DBS trips' origins and destinations with kernel density illustrated by the heatmap. Four polygons are parking rings with a size of 100 m, 300 m, 500 m, and 1000 m, respectively. The orange polygon is selected as the optimal (500 m). Panel (b) depicts how $\widetilde{D}_{r,k}$ varies as the distance (r) changing from 25 m to 1000 m with the step of 25 m.

available.

3.3.2. Assessment of BnR performance

We employed four metrics to comprehensively understand the BnR behaviors from the perspectives of different participators. Specifically, the four metrics are described as follows:

1) BnR trip count measures how many BnR trips are generated near a metro station, which is the most intuitive and widely employed metric to assess the DBS usage as well as their occupied public spaces (Chen et al., 2017; Guo et al., 2021).
2) Shared-bike utilization rate is the normalization of BnR trip count with the number of shared bikes as the denominator, which indicates how many BnR trips are generated by each shared bike on average (Li et al., 2020; Shen et al., 2018). Shared-bike utilization rate measures the usage efficiency of shared bikes, eliminating the endogeneity biases caused by the shared-bike allocation process (similar to the station installation process biases in docked bike-sharing system (Faghih-Imani and Eluru, 2016a)).
3) Metro catchment area is measured as the area that metro services can be accessed by cycling. Similar to prior studies (Li et al., 2021; Wu et al., 2021), the size of the catchment area is defined by the 85th percentile of the cumulative distribution of the egress or access network distances to each metro station. Catchment size serves as a proxy of accessibility to the metro via DBS. A larger catchment size implies a longer transfer distance and poorer accessibility.
4) BnR rate represents the proportion of metro passengers choosing BnR (Ma et al., 2018b), which measures the joint efficiency of the BnR system, offsetting simultaneity biases between metro ridership and nearby DBS usage.

The four metrics describe BnR activities from different perspectives. DBS operators may feel interested in BnR trip count and shared-bike utilization rate, local governments may feel interested in metro catchment size and BnR rate, while DBS users may care more about shared-bike utilization rate and metro catchment size. Jointly analyzing the four metrics can uncover more information. For example, a metro station with a higher BnR trip count but lower shared-bike utilization rate indicates an oversupplied state; a metro station with a lower BnR trip count but higher shared-bike utilization rate denotes an undersupplied situation but may not have the potential to generate substantial trips, and a metro station with both higher BnR trip count and higher shared-bike utilization rate indicates an undersupplied situation but with promising potential to become a hotspot if supply is adequate.

Considering we did not have sufficient data at a longitudinal level (only five-day data is available), in this study we only conducted the cross-sectional analysis with all metrics averaged at a daily level. The four metrics were calculated as Eqs. (3–6). Further studies could consider the temporal variance, for example, differences between morning peak, afternoon peak, and off-peak, or differences between weekdays and weekends, if sufficient data are accessible.

$$N_k = \sum_{i=1}^{n_k} I\left(min\left(d_{O_i,k}, d_{D_i,k}\right). < 500\right) \tag{3}$$

$$T_k = \frac{N_k}{\left|\left\{B_i | min\left(d_{O_i,k}, d_{D_i,k}\right). < 500\right\}\right|} \tag{4}$$

$$C_k = Q_{0.85}\left(d_{O_i,D_i} | min\left(d_{O_i,k}, d_{D_i,k}\right). < 500\right) \tag{5}$$

$$BnR_k = \left(\frac{\sum_{i=1}^{n_k} I\left(d_{O_i,k} < 500\right)}{AT_k} + \frac{\sum_{i=1}^{n_k} I\left(d_{D_i,k} < 500\right)}{BD_k}\right) \Big/ 2 \tag{6}$$

where N_k is the BnR trip count at metro station k; $d_{Oi,\ k}$, $d_{Di,\ k}$, n_k are the same as those in Eqs. (1–2); T_k is the shared-bike utilization rate at metro station k; B_i is the bike ID of trip i; $|.|$ is the size of a set; C_k is the catchment size; $Q_{0.85}(.)$ is the 0.85 quantile; $d_{Oi,\ Di}$ is the length of trip i measured by network distance; BnR_k is the BnR rate at metro station k; AT_k and BD_k are the number of passengers alighting and boarding at metro station k, respectively.

Fig. 4 illustrates how selected BnR trips near a metro station are distributed spatially, as well as the physic representative of the catchment area and optimal parking ring. The summary of four metrics is reported in Table 1. The average number of daily BnR trips was 3577.86 near each metro station but in high dispersion ranging from 107.50 to 13,480.25. In addition, one shared bike on average generated 1.38 BnR trips each day. It is worth noting that the shared-bike utilization rate here was calculated only based on BnR trips. The utilization rate considering all DBS trips was greater, which was 2.26 trips per day. Data also revealed that 13% of metro passengers chose DBS as their transfer mode. Similar values were documented in prior studies. For example, one recent study based on a questionnaire survey in Shenzhen, China concluded that around 13% of people chose DBS as their feeder mode of metro (Guo and He, 2021a).

3.3.3. Generalized additive model

The generalized additive model (GAM) (Wood, 2006) was employed to construct statistical inference. GAM is a semi-parametric model with linear predictors involving a series of additive non-parametric smoothers of covariates. Also, the distribution of dependent variables is not limited to Gaussian and varies with data characteristics. Compared to the ordinary least squares (OLS) linear regression, GAM is more flexible with fewer assumptions, which is useful when data fail to meet OLS assumptions, such as normality and homogeneity. Additionally, a noticeable advantage of GAM lies in its capability and flexibility to handle different nonlinear effects (Wood, 2006). By changing spline functions, a variety of nonlinear effects such as nonlinear interactions and spatial dependence can be fitted under one framework (Hu et al., 2018; Wang et al., 2020).

When modeling DBS usage, over-dispersion, skewness, and spatial autocorrelation are several main statistical issues that need to be addressed (Guo et al., 2021; Hu et al., 2021b; Noland et al., 2016). Similar to prior studies (Guo and He, 2020; Hu et al., 2021b), we assumed BnR trip count follows a count-based negative binomial (NB) distribution, while BnR rate follows a Gamma distribution with log-link. Compared with Poisson distribution, NB distribution introduces an additional free parameter to relax the assumption that expectation and variance are equal, which can well solve the over-dispersion problem. Similarly, compared with normal distribution, Gamma distribution has more flexible shapes and has a property shared by the lognormal but avoids transformation bias, which is more suitable for data that are continuous, positive, and right-skew. Besides NB distribution, we also tested other distributions for comparison. For count data (i.e. BnR trip count), we tested Poisson distribution, and for continuous data (i.e. shared-bike utilization rate, catchment size, and BnR rate), we tested normal distribution. Models with the lowest AIC were chosen as the optimal options and listed in Eq. (7).

To capture the spatial dependence, an additive term to fit the spatial coordinate interaction was attached (Wood, 2017). Prior studies have proved that such a term can eliminate the spatial autocorrelation in residuals (Hu et al., 2018). We also involved some nonlinear interactions between variables of interest via the marginal nonlinear smoothers with the exclusion of the basic functions associated with main effects (Wood, 2006), which provides a stable and interpretable way of specifying models with main effects and interactions separately. The final formulations of the four GAMs are as follows:

$$Y^{(1)} \sim NB\left(\mu_1 \mu_1 + \frac{{\mu_1}^2}{k_1}\right), Y^{(2)} \sim Gamma\left(\mu_2 \frac{{\mu_2}^2}{k_2}\right), Y^{(3)} \sim N\left(\mu_3 {\sigma_3}^2\right), Y^{(4)} \sim N\left(\mu_4 {\sigma_4}^2\right) \tag{7}$$

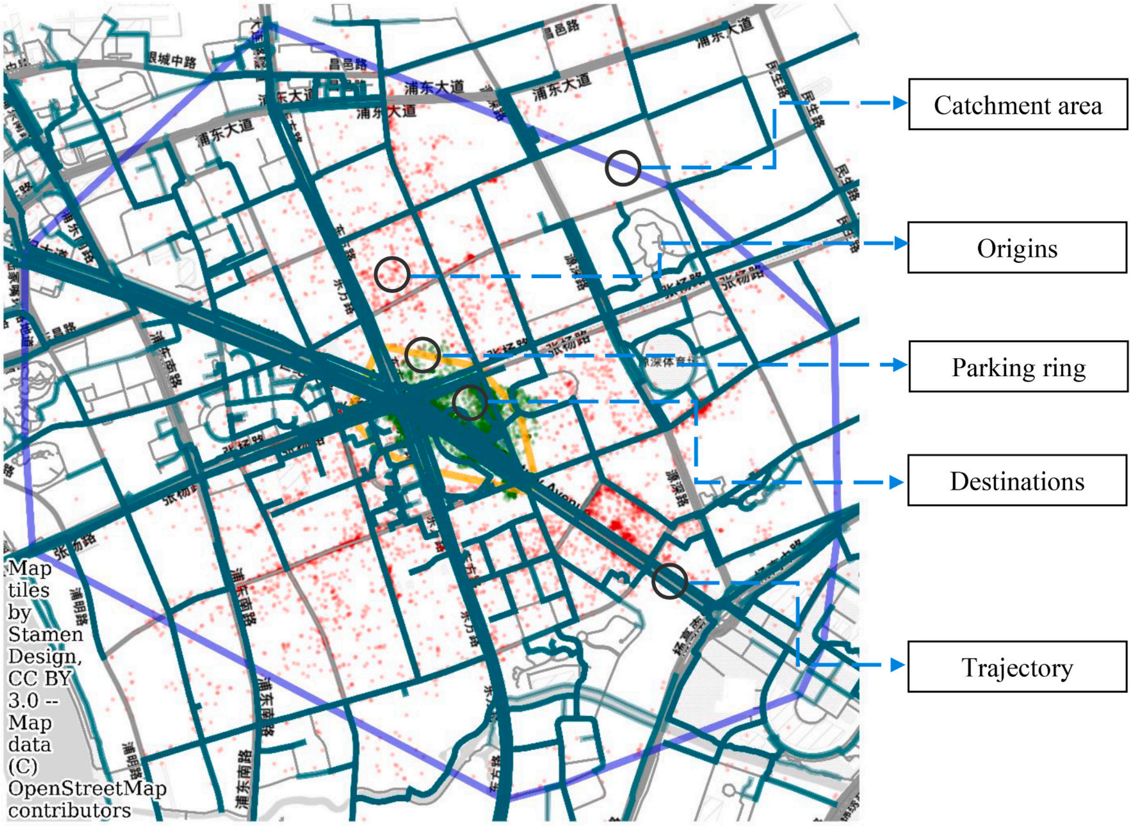


Fig. 4. Map of BnR trips. Century Avenue metro station is depicted. Each green spot represents the destination of a BnR trip, with the red spot as its origin. Orange polygon is the optimal 500 m parking ring used to filter the BnR trips. Blue polygon is the catchment area with a size equal to 85 percentile of riding network distance. Dark green lines above the network are the riding trajectory estimated by Dijkstra's algorithm. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$$g^{(r)}\left(Y_i^{(r)}\right) = \beta_0{}^{(r)} + \sum_{m=1}^{M} \beta_m{}^{(r)} X_{m,i} + \sum_{(p,q)\in\boldsymbol{\omega}} f_{X_pX_q|\boldsymbol{X}_{1:M}}\left(X_{p,i}\times X_{q,i}\right) + \widetilde{S}_i + \vartheta_i{}^{(r)} \tag{8}$$

where $Y^{(1)}$, $Y^{(2)}$, $Y^{(3)}$, $Y^{(4)}$ are daily average BnR trip count, shared-bike utilization rate, catchment size, and BnR rate, respectively; μ_1, μ_2, μ_3, μ_4 are the mean of $Y^{(1)}$, $Y^{(2)}$, $Y^{(3)}$, $Y^{(4)}$; k_1, k_2 are distribution scaling parameters; $\mu_1 + \frac{\mu_1^2}{k_1}, \frac{\mu_2^2}{k_2}, \sigma_3, \sigma_4$ are standard deviations of $Y^{(1)}$, $Y^{(2)}$, $Y^{(3)}$, $Y^{(4)}$; $g^{(r)}(.)$ is the link function of the r^{th} dependent variable $Y^{(r)}$, where r = 1,2,3,4; when $Y^{(r)}$ follows the NB or Gamma distribution, $g^{(r)}(.)$ is log-link, and when $Y^{(r)}$ follows the normal distribution, $g^{(r)}(.)$ is identity link; $\beta_0{}^{(r)}$ is the overall intercept for the r^{th} dependent variable; $\beta_m{}^{(r)}$ is the coefficient of the m^{th} independent variables X_m, and M is the number of independent variables with fixed effects; X_p and X_q are the pair of independent variables with nonlinear interactions; $\boldsymbol{\omega}$ is the set of variable pairs nonlinearly interacted with each other; $f_{X_pX_q|\boldsymbol{X}_{1:M}}(.)$ is the marginal nonlinear smoother excluding the main effects from the set of independent variables $\boldsymbol{X}_{1:M}$ fitted in fixed effects term (Wood, 2006); $\widetilde{S}_i$ is the spatial coordinate interaction of station i; $\vartheta_i{}^{(r)}$ is the error term.

3.3.4. *Independent variable and modifiable area unit problem*

Independent variables are the external environment surrounding each metro station, including land use, socio-demographics, roadway designs, transportation facilities, station features, and operator features. Among them, land use was obtained from Shanghai Municipal Land Use Planning and Gaode Map Point-of-interests (POIs), socio-demographics were identified using China's 6th Nationwide Population Census, roadway designs were calculated based on road network from Open Street Map, station features were obtained from Shanghai Metro Bureau, and carsharing information was obtained from the biggest carsharing system named EVCARD in Shanghai (Hu et al., 2021a). For operator features, we only include the top three biggest due to high multicollinearity if other operators are included. The other five operators with small scales are thus set as reference. We also did not incorporate the price information since differences in their price strategies are minor. Most operators collected 1 ¥ for hourly rental and 20 ¥ for monthly membership.

Variable selection was performed to determine the optimal variable set. The variance inflation factor (VIF) was first calculated to test the multicollinearity, and VIFs greater than 5 were excluded. Then, a forward stepwise regression was used to select the optimal independent variables based on the smallest AIC. In addition, to eliminate the effects of outliers, we excluded influential outliers by removing the observations if their Cook's distance exceeded the cutoff value $4/(n-k-1)$, where n is the sample size and k is the number of independent variables (Belsley et al., 2005). The summary of independent variables is reported in Table 1. Variables in the *Italic* text were excluded from models, either because of the high multicollinearity with other variables or the low capability in explaining dependent variables. It is worth mentioning the VIF test and stepwise selection did not yield the same optimal set for the four models. For the convenience of comparison, we used the union of the four sets of optimal variables as the final variable set.

All independent variables were calculated via the spatial join between the buffer of the metro station and other shapefiles containing the information of interest. One concern is regarding the modifiable area unit problem (MAUP), which postulates that different buffer sizes may lead to different modeling results (Gao et al., 2021). Previous studies generally employed the catchment area as the buffer to calculate the

Table 1
Summary of variables.

		Description	Mean	St.d.	Median	Min.	Max.
Dependent variables							
BnR trip count	Daily average number of BnR trips near a metro station		3577.86	2801.42	3137.75	107.50	13,480.25
Shared-bike utilization rate	Daily average shared bike utilization rate near a metro station		1.38	0.15	1.35	1.09	1.97
Catchment size	Average size of metro catchment area (85th percentile of transfer distance in network), in km		2.19	0.43	2.07	1.53	4.00
BnR rate	Average BnR rate in a metro station		0.13	0.12	0.11	0.00	1.07
Independent variables (buffer size: 1500 m)							
Land use (Buffer-level)	Agriculture	Proportion of agriculture land	0.03	0.07	0.00	0.00	0.42
	Commercial	*Proportion of commercial land*	0.02	0.03	0.00	0.00	0.17
	Industry	Proportion of industry land	0.09	0.10	0.05	0.00	0.66
	Office	Proportion of office land	0.01	0.01	0.00	0.00	0.07
	Public	Proportion of public land	0.10	0.07	0.09	0.00	0.41
	Residence	Proportion of residential land	0.33	0.15	0.36	0.00	0.69
	Education	*Proportion of education land*	0.06	0.05	0.05	0.00	0.34
	Green space	*Proportion of green space*	0.03	0.04	0.02	0.00	0.29
	College	Number of colleges, in counts	8.09	15.10	2.00	0.00	102.00
	Shopping mall	Number of shopping malls, in counts	7.96	10.90	4.50	0.00	70.00
	Tourist attraction	Number of tourist attraction, in counts	20.55	32.23	8.00	0.00	193.00
	LUM [a]	Entropy of land use, varying from 0 (homogeneous) to 1 (most mixed)	0.74	0.08	0.74	0.47	0.89
Socio-demographic (Subdistrict-level)	Population density	Population density, in 10^4 persons/sq. km	2.00	1.52	1.63	0.09	9.73
	Female	*Proportion of female residents*	0.49	0.02	0.49	0.40	0.55
	Age under 15	Proportion of residents 15 years and less	0.08	0.02	0.08	0.01	0.12
	Age 16–64 (Reference)	*Proportion of residents 16 to 65 years*	*0.80*	*0.04*	*0.81*	*0.57*	*0.97*
	Age over 65	Proportion of residents 65 years and over	0.11	0.05	0.11	0.01	0.35
Roadway design (Buffer-level)	Primary road	Length of primary road, in km	7.44	4.93	6.79	0.00	21.91
	Secondary road	*Length of secondary road, in km*	6.72	5.28	5.68	0.00	34.35
	Tertiary road	Length of tertiary road and residential road, in km	21.18	15.86	16.81	0.23	100.03
	Cycleway	Length of cycleway and pathway, in km	4.17	6.66	1.42	0.00	39.15
Station features (Station-level)	Terminal station	If a station is a terminal station,1; else 0	0.07	0.25	0.00	0.00	1.00
	Distance to city center	Distance between a metro station and the city center (the People's Square), in km	10.27	6.69	8.78	0.00	34.73
	Metro lines	Number of metro lines passing through the metro station, in counts	1.26	0.57	1.00	1.00	4.00
	Metro ridership	Daily average number of metro passengers (boarding and alighting), in 10^4 persons	3.35	2.50	2.75	0.21	17.61
	Distance to closest metro station	Distance between a metro station and its closest metro station, in km	1.19	0.73	1.00	0.34	9.94
Transportation facilities (Buffer-level)	Bus stops	Number of bus stops, in counts	30.01	16.88	28.00	2.00	97.00
	Bus lines	*Number of bus lines, in counts*	94.68	58.90	91.00	3.00	283.00
	Carsharing stations	Number of carsharing stations, in counts	4.93	4.52	4.00	0.00	26.00
	Carsharing parking lots	*Number of carsharing parking lots, in counts*	28.84	25.93	22.50	0.00	154.00
Operator features (Buffer-level)	Ofo	Proportion of trips generated by Ofo bikes	0.59	0.12	0.57	0.25	0.91
	Mobike	Proportion of trips generated by Mobike bikes	0.31	0.10	0.33	0.05	0.57
	Xiangqi	Proportion of trips generated by Xiangqi bikes	0.05	0.04	0.05	0.00	0.21
	Operators	Number of bikesharing operators, in counts	4.00	0.36	4.00	3.00	5.00

Note: a. The land-use mixture (LUM) is measured by:

$$LUM = \begin{cases} -(1/lnN)\sum_{i=1}^{N} p_i ln p_i, & N > 1 \\ 0, & N = 1 \end{cases} \quad (9)$$

where N is the number of land use types in the optimal buffer and p_i is the proportion of land of type i in the optimal buffer.

surrounding built environment (Guo and He, 2020; Li et al., 2021). However, there is currently no evidence showing that using the catchment area can obtain the optimal model fit. To obtain the optimal buffer size as well as to check the robustness of model estimations, we calculated independent variables under different buffers with sizes varying from 100 m to 2000 m with a step of 100 m. All buffers are defined by the concave hull of reachable nodes under specific buffer size measured by network distance. Then, we fitted GAMs with independent variables calculated under those buffers and selected the buffer exhibiting the best model goodness-of-fit as our final aggregation unit. To statistically ensure the robustness of model performance, model goodness-of-fit under each buffer size was calculated via 500 bootstraps and the corresponding median was used as the final measurement. It is worth mentioning that the four BnR metrics' models may have different optimal buffer sizes. For brevity, only the summary of variables calculated by 1500 m buffer size is reported in Table 1 here. More detailed results are reported in Section 4.3 and Supplementary Table S1-S4.

4. Results

4.1. Spatial distribution of four BnR metrics

Spatial distributions of metro station-level BnR metrics are mapped in Fig. 5. A pronounced relationship between the four metrics and the distance to the city center can be observed, which is consistent with Fig. 1. Specifically, the four metrics' Pearson correlations with distance to city center were − 0.646 (BnR trip count), −0.519 (BnR rate), 0.481 (shared-bike utilization rate), and 0.602 (catchment size), respectively, with all P-values <0.001. BnR trip count and BnR rate exhibited similar spatial patterns. They both presented higher values near the city center and lower values in the suburb. On the contrary, shared-bike utilization rate and catchment size showed a reversed pattern against BnR trip

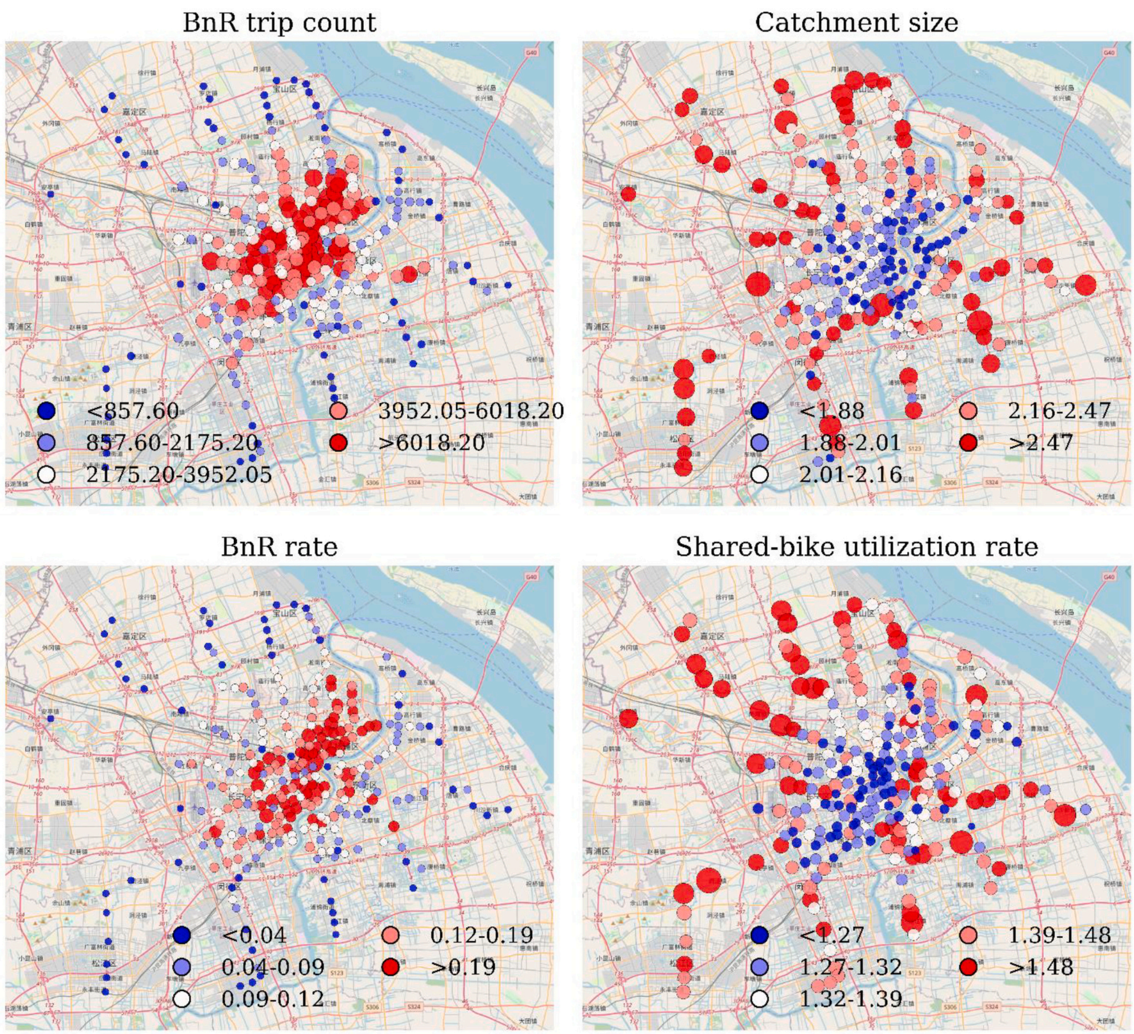


Fig. 5. Spatial distribution of four BnR metrics. The size of dot is proportional to the magnitude of metrics. Cooler and warmer colors imply less or greater value of metrics.

count and BnR rate. They both presented lower values near the city center and higher values in the suburbs. The spatial distributions of four metrics jointly indicated that shared bikes were oversupplied in the city center while undersupplied in the suburb. Shared bikes located in the suburb were used more frequently. Meanwhile, riders had to walk longer to find shared bikes and ride longer to access the metro station.

4.2. Outputs of optimal GAMs

Results of GAMs under optimal buffer sizes are listed in Table 2. Two parts were included in each model: the parametric coefficients, corresponding to linear fixed effects, and the nonparametric smooth terms, corresponding to nonlinear effects. Model goodness-of-fit index, *Dev. Explained*, which is the proportion of the null deviance explained by the model, were 0.87, 0.72, 0.85, 0.70, respectively, implying the GAMs fitted the data well. We also reported the adjusted R^2 as another goodness-of-fit index, however, since distributions of the four GAMs were different, the adjusted R^2 cannot be compared directly across models.

4.2.1. Linear fixed effects

Among socio-demographic features, proportion of residents 15 years was significantly negatively associated with BnR trip count and BnR rate, while the other two variables, the population density and the proportion of residents over 65, did not exhibit significant relationships with the four metrics. Among land-use features: 1) proportion of public and residential land was significantly positively associated with BnR trip count and negatively associated with catchment size; 2) proportion of agriculture land was significantly negatively related to shared-bike utilization rate and BnR rate; 3) LUM and number of colleges and shopping malls were significantly positively related to BnR trip count; 4) number of colleges was significantly positively associated with BnR rate and shared-bike utilization rate, number of shopping malls was significantly positively associated with shared-bike utilization rate; 5) other land use, such as industrial land, office land, and tourist attractions, did not present significant associations with four BnR metrics.

Regarding two transportation facilities, the number of bus stops showed significant and positive relationships with shared-bike utilization rate. Number of carsharing stations presented significant and positive relationships with BnR trip count and BnR rate. Among station features: 1) metro ridership presented significantly positive relationships with BnR trip count and shared-bike utilization rate, and presented significantly negative relationship with BnR rate; 3) terminal station was statistically positively associated with catchment size; 4) number of metro lines was statistically positively associated with BnR rate; 5) distance to the city center was positively associated with catchment size and shared-bike utilization rate, and was negatively associated with BnR trip count and BnR rate. For roadway design, length of primary roads and tertiary roads was significantly negatively associated with catchment size. Length of tertiary roads was also significantly positively

Table 2
Outputs of GAMs.

		BnR trip count (1500 m)	Catchment size (1000 m)	BnR rate (1500 m)	Shared-bike utilization rate (1000 m)
Parametric coefficients					
	(Intercept)	3.28*** (1.77, 4.79)	1.43*** (1.03, 1.84)	−3.14*** (−4.71, −1.58)	0.06 (−0.22, 0.34)
Socio-demographic	Population density	0.04 (−0.04, 0.12)	0.00 (−0.01, 0.02)	0.02 (−0.07, 0.12)	−0.03 (−0.05, 0.01)
	Age 16–64	−0.63 (−2.08, 0.82)	−0.32 (−0.73, 0.09)	−1.11 (−2.52, 0.30)	0.16 (−0.12, 0.44)
	Age under 15	−7.09*** (−10.99, −3.19)	−0.70 (−1.79, 0.40)	−7.65*** (−11.45, −3.84)	−0.47 (−1.19, 0.26)
Land use	Industry	0.13 (−0.56, 0.82)	−0.18. (−0.34, 0.02)	−0.31 (−1.02, 0.41)	−0.10. (−0.20, 0.01)
	Office	−0.60 (−5.42, 4.22)	−0.37 (−1.41, 0.68)	−3.50 (−8.34, 1.33)	−0.41 (−1.06, 0.24)
	Public	1.36** (0.38, 2.34)	−0.38** (−0.60, −0.15)	1.02. (−0.01, 2.05)	−0.00 (−0.15, 0.15)
	Agriculture	−0.82 (−2.01, 0.36)	0.03 (−0.21, 0.27)	−1.30* (−2.55, −0.05)	−0.15* (−0.31, −0.02)
	Residence	1.04*** (0.45, 1.64)	−0.26*** (−0.38, −0.14)	−0.10 (−0.69, 0.49)	0.07. (−0.00, 0.15)
	LUM	0.41* (0.35, 1.16)	0.01 (−0.16, 0.18)	−0.11 (−0.85, 0.64)	0.02 (−0.08, 0.13)
	College	0.01*** (0.00, 0.01)	−0.00. (−0.00, 0.00)	0.01** (0.00, 0.01)	0.00** (0.00, 0.00)
	Tourist attraction	−0.00 (−0.01, 0.00)	0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)
	Shopping mall	0.01* (0.00, 0.02)	0.01 (−0.00, 0.01)	0.01* (0.00, 0.02)	0.00 (−0.00, 0.00)
Transportation facilities	Bus stops	0.00 (−0.00, 0.01)	−0.00. (−0.01, 0.00)	0.01. (−0.00, 0.01)	0.00** (0.00, 0.01)
	Carsharing stations	0.02** (0.01, 0.04)	0.00 (−0.01, 0.01)	0.02* (0.00, 0.03)	0.00 (−0.00, 0.01)
	Distance to closest metro station	−0.07 (−0.17, 0.02)	0.01 (−0.02, 0.03)	−0.09 (−0.21, 0.04)	0.02 (−0.00, 0.04)
Station features	Metro ridership	0.10*** (0.07, 0.12)	0.00 (−0.00, 0.01)	−0.16*** (−0.18, −0.13)	0.00* (0.00, 0.01)
	Terminal station	0.15 (−0.06, 0.36)	0.08* (0.02, 0.14)	0.01 (−0.21, 0.22)	−0.01 (−0.05, 0.03)
	Metro lines	0.01 (−0.08, 0.11)	0.01 (−0.02, 0.04)	0.16*** (0.07, 0.26)	−0.01 (−0.03, 0.01)
	Distance to city center	−0.07*** (−0.09, −0.04)	0.00* (0.00, 0.01)	−0.05** (−0.08, −0.01)	0.01** (0.00, 0.02)
Roadway design	Primary road	0.00 (−0.01, 0.02)	−0.01** (−0.01, −0.00)	0.01. (−0.00, 0.02)	0.00 (−0.00, 0.01)
	Tertiary road	0.01*** (0.00, 0.02)	−0.01*** (−0.01, −0.00)	0.01** (0.00, 0.01)	0.00** (0.00, 0.00)
	Cycleway	−0.01 (−0.02, 0.00)	−0.00 (−0.01, 0.00)	−0.01. (−0.02, 0.00)	−0.00 (−0.01, 0.00)
Operator features	Mobike	3.38*** (2.20, 4.55)	−0.27 (−0.60, 0.06)	1.22* (0.03, 2.41)	0.05 (−0.17, 0.27)
	Ofo	2.78*** (1.55, 4.01)	−0.42 (−0.77, 0.07)	1.10* (0.06, 2.37)	0.00 (−0.23, 0.24)
	Xiangqi	7.40*** (5.36, 9.44)	−0.12 (−0.69, 0.45)	5.18*** (3.08, 7.27)	−0.25 (−0.62, 0.13)
	Operators	0.13 (−0.04, 0.30)	−0.04 (−0.09, 0.01)	0.02 (−0.16, 0.20)	0.01 (−0.02, 0.04)
Smooth terms					
		e.d.f.	e.d.f.	e.d.f.	e.d.f.
ti (Longitude, Latitude)		4.67***	2.17*	15.15***	11.00***
ti (Distance to city center, Population density)		6.60***	1.00	7.56***	1.55
Mode fit					
Dev. explained		0.87	0.72	0.86	0.70
Adj. R^2		0.69	0.60	0.69	0.57

Note: Robust 95% confidence interval (CI) is in parentheses. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ''1. P-value <0.05 is considered as statistically significant. ti() means the marginal nonlinear interaction function.

associated with BnR trip count, BnR rate, and shared-bike utilization rate. Last, for operator features, market shares of Mobike, Ofo, and Xiangqi all presented significant and positive relationships with BnR trip count and BnR rate. Note that directly comparing the magnitude of coefficients is not meaningful here since our model is unstandardized.

4.2.2. *Nonlinear effects*

As for nonlinear effects, spatial interaction terms were all statistically significant and degrees of freedom (e.d.f.) were all largely greater than 1, implying that the GAMs well captured the spatial nonlinear interactions. Moreover, the nonlinear interactions between distance to the city center and population density in modeling BnR trip count and BnR rate both showed high significance and with degrees of freedom larger than 1, indicating metro station's distance to the city center and surrounding population density jointly affected BnR trip count and BnR rate with significance. The nonlinear interactions in the other two models did not show significant degrees of freedom.

The marginal nonlinear interactions of the two models with significance are delineated in Fig. 6. Numbers on the contours are the logarithmic marginal effects of the interacted variables on the corresponding metric (see Eq. (7–8) for more information). Through the contours, we documented a reversal in the ordering of BnR activities using DBS by population density: regions with higher population density went from fewer BnR trips and lower BnR rate near the city center to more BnR trips and higher BnR rate away from the city center. Such reversal was more salient regarding the BnR rate compared with the BnR trip count when the distance to the city center was large. It is worth noting that marginal interactions shown in Fig. 6 have excluded the main effects which were captured in fixed-effect parts. Therefore, we could not observe an apparent negative relationship between DBS usage and distance to the city center as such effects have already been captured by the significantly negative coefficients in fixed effects.

4.3. GAMs under different buffer sizes

As discussed in Section 3.3, to find the optimal buffer size, we tested different sizes to calculate independent variables and fitted GAMs accordingly. Model goodness-of-fit under different buffer sizes are reported in Fig. 7. We found the goodness-of-fit of modeling BnR trip count and BnR rate presented similar patterns. They all steeply increased at first until reaching the peak at 1500 m, followed by a persistent decrease. The goodness-of-fit of modeling catchment size and shared-bike utilization rate presented a similar pattern. It increased at first until reaching the peak at 1000 m, followed by a stable plateau or slow decrease thereafter.

Through Fig. 7 we can conclude that when modeling BnR trip count and BnR rate, the optimal buffer size to calculate surrounding independent variables is 1500 m; when modeling catchment radius and shared-bike utilization rate, the optimal buffer size is 1000 m. One explanation is that 1000 m – 1500 m is the cut-off range of transfer distance when cycling is the most attractive option. People may choose to walk when the network distance is shorter than 1000 m and prefer other motorized options when the network distance is longer than 1500 m. Such value is also broadly in line with previous studies with buffer sizes varying from 500 m to 2000 m (Guo and He, 2020; Guo et al., 2021; Hu et al., 2021b).

Results of GAMs under different buffer sizes are reported in Supplementary Table S1-S4. Comparing coefficients across models under different buffer sizes, we found most estimations remained robust, both in terms of their significance and signs. However, we did find some changes in the significance of coefficients, which may account for the variation in model goodness-of-fit. For example, with the increase of buffer size, some variables changed from insignificant to significant, including the LUM and the number of nearby carsharing stations. Such change may explain why performances of modeling these metrics increased with the increase of buffer size. On the other hand, some variables in modeling catchment size became insignificant as buffer size increased, for example, the proportion of public land and the number of shopping malls, which may account for the decrease in performance of modeling catchment size as buffer size increases.

5. Discussion

As expected, compared with residents aged 16 to 64, a higher proportion of residents aged under 16 is negatively correlated with BnR trip count and BnR rate. It is plausible since in China youth under 12 (16) are prohibited to ride shared (electric) bikes by law. Unlike previous studies (Chen et al., 2017; Chen et al., 2021; Guo et al., 2021; Li et al., 2020), we did not find a significant monotonous relationship between BnR activities using shared bikes and population density. To identify the reason, we delineated the marginal nonlinear interactions between distance to the city center and population density. We documented a reversal in the ordering of BnR frequency using DBS by population density when moving from the city center to suburban areas. Metro stations located in higher population density regions go from fewer BnR trips and lower BnR rates near the city center to more BnR trips and higher BnR rates away from the city center. Such findings are in accordance with previous studies suggesting substantial differences in model estimations between the city center and suburb via geographically weighted regression models (Ji et al., 2018; Li et al., 2021). A possible explanation is that regions with higher population density in the city center own a well-developed transport system. Thus, residents have more options to choose from, which may dwarf the attractiveness of using DBS to BnR. Additionally, those areas are mainly occupied by high-income groups, who rely more on private cars and have less cycling demand (Ji et al., 2018; Ma et al., 2018b). Moreover, the high land price and tight land use restriction in those areas may further curtail the capacity of DBS operators to launch shared bikes. On the contrary, areas with higher population density but located in the suburbs are not well served by traditional transport systems but with higher commuting demand and

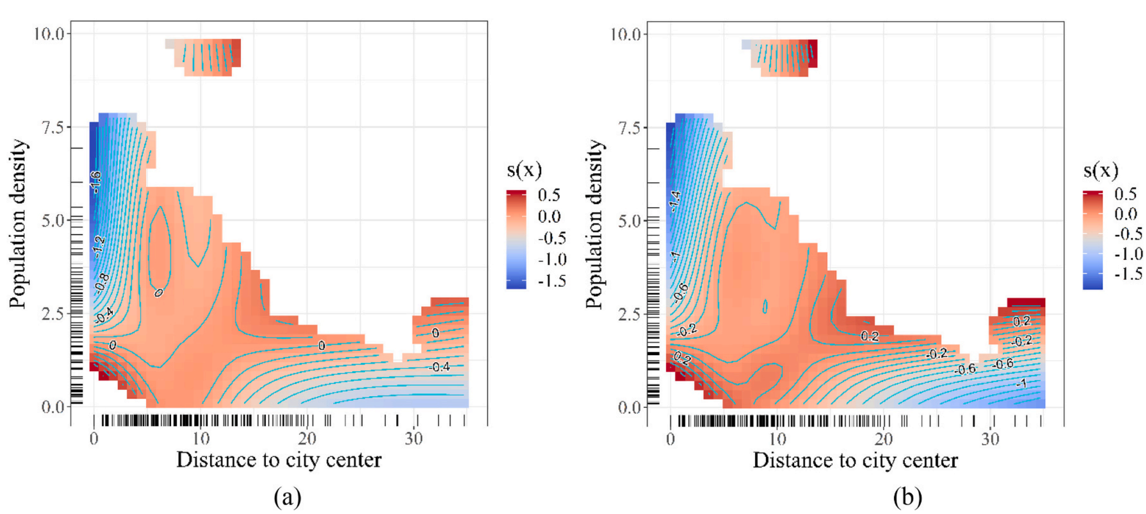


Fig. 6. Marginal nonlinear interactions between Distance to city center and Population density. Each contour depicts a metric from (a) BnR trip count and (b) BnR rate.

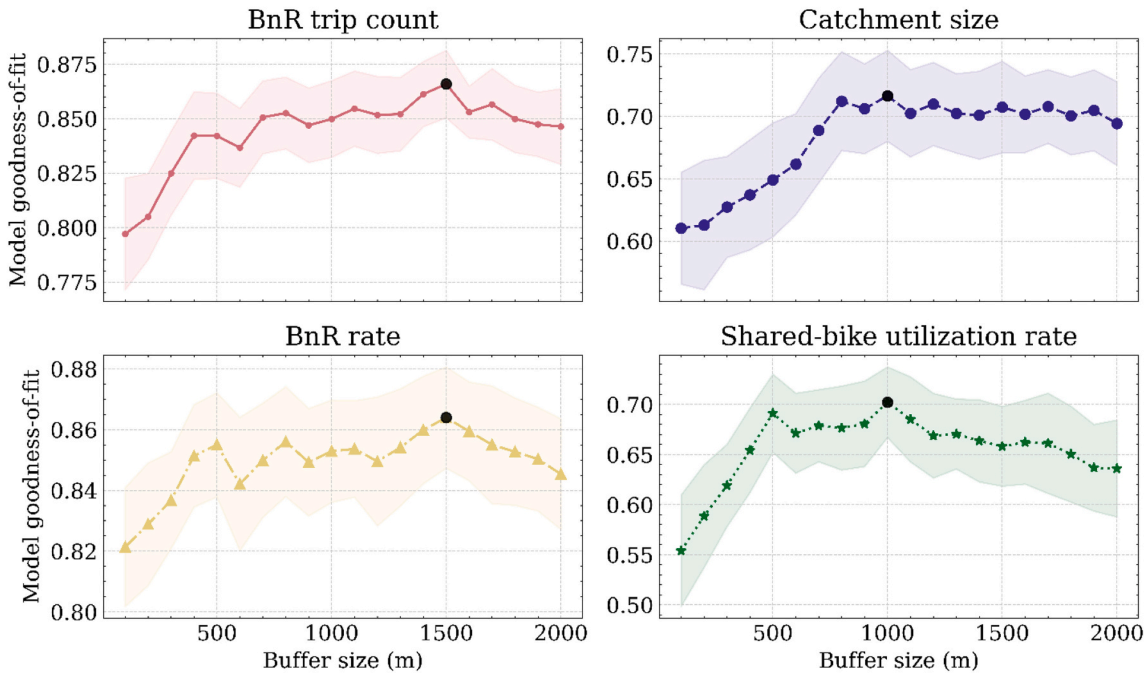


Fig. 7. Model goodness-of-fit (Dev. explained) of four BnR metrics under different buffer sizes. Each curve represents one metric. The greatest model goodness-of-fit was marked by the black dot. Buffer denotes the 95% CI obtained via 500 bootstraps.

looser DBS restrictions. Hence, these areas are more likely to grow into the hotspots of DBS.

Land use presents substantial but diverse associations with four BnR metrics. We found locating shared bikes around metro stations with more public and residential land or higher land use mix can create positive externalities on BnR frequency using DBS, both in terms of boosting BnR trip count and reducing transfer distance. These findings are consistent with prior studies (Chen et al., 2018; Guo et al., 2021; Noland et al., 2016; Tu et al., 2019). However, after offsetting the metro ridership, most of the land use types did not present significant associations with the BnR rate. This indicates the BnR rate is less influenced by land-use types — perhaps other unobserved socio-economic factors such as household car ownership and median income account more (Ji et al., 2017; Mooney et al., 2019). In addition, we found shared bikes around metro stations with more agricultural land exhibit significantly lower utilization rates and BnR rates. It is intuitive since few travels are generated from or to agricultural land.

Similar to previous studies (Ji et al., 2018; Li et al., 2020; Xing et al., 2020), some types of POIs are also significantly related to BnR. We noticed DBS is more popular in metro station areas with college presenting, manifesting as more DBS trips, higher BnR rate, and higher shared-bike utilization rate. College students are always considered the majority of cyclers, as most of them do not own private cars and have no income (Mattson and Godavarthy, 2017; Schimohr and Scheiner, 2021). In Shanghai, it costs ¥ 1 for riding a shared bike, ¥ 2 for riding a bus, and ¥ 3 for riding the metro within 6 km, among which DBS is the most cost-effective option. We also observed shopping malls near the metro station can attract more DBS trips, which is plausible since shopping malls always have high trip attraction rates (Schimohr and Scheiner, 2021; Xing et al., 2020).

Among transportation facilities, we found a significant relationship between the number of bus stops and shared-bike utilization rate. We also observed a significant positive relationship between the number of carsharing stations and BnR activities using DBS. However, it would be inappropriate at this stage to interpret these relationships as causal, for example, stating carsharing and bus can motivate people to BnR using DBS, since it could also be due to carsharing and bus operators are following the same rules in allocating their stations as DBS operators do. Nonetheless, such a finding highlights the potential of promoting mobility efficiency through the integration of different shared mobility including carsharing, bikesharing, and transit (Hu et al., 2018).

Regarding station features, consistent with previous studies (Guo and He, 2020; Guo et al., 2021; Li et al., 2021), metro passenger ridership indicates a positive association with BnR trip count and shared-bike utilization rate. However, it presents a negative relationship with the BnR rate, which may be due to the BnR rate is calculated by using metro ridership as the denominator. The number of metro lines is significantly positively associated with BnR rate, since metro stations with multiple lines intersected are more likely to be a regional transfer center. In contrast, terminal stations are mainly located in suburban areas where the number of shared bikes is limited and road density is low, leading to a longer transfer distance. Last, the distance to the city center presents significant relationships with all BnR metrics. The greater BnR trip count but lower shared-bike utilization rate near the city center jointly indicate an oversupply situation of DBS resources in urban areas. The larger catchment size in the suburb further uncovers a disproportionate distribution of mobility services: people in the suburb have to ride longer to access a metro station, either due to the sparse metro network or the deficient shared bikes (Ji et al., 2018; Li et al., 2021).

Among roadway designs, a higher density of tertiary roads is positively correlated with bike usage. Also, a higher density of primary and tertiary roads is negatively associated with catchment size. Regions with denser road networks indicate high accessibility and connectivity, and thus can shorten the transfer distance (Chen et al., 2017; Li et al., 2021). Such findings suggest a possible solution to offset the poor accessibility through intensifying roads especially in suburban areas. Interestingly, we did not observe a significant relationship between cycleways and four metrics, implying a weak attractiveness of cycleways to DBS riders. This is perhaps because bike riders in Shanghai are not only restricted to cycleways. Indeed, riders can cycle along almost all roads except highways on the non-motorized lanes placed on roadsides. The government is suggested to further enhance the friendliness and attractiveness of cycleways to non-motorized travelers via installing protective infrastructure, intensifying road density, and increasing greenbelt coverage.

Usage shares of the top three DBS operators all showed significant positive relationships with BnR frequency and BnR rate. This implies large DBS operators substantially outperformed small ones at least regarding their popularity in BnR. A successful DBS program needs a certain scale, which ensures the spatial access of bikes for mass users and benefits from the scale economies. However, none of these large DBS operators performed a significant relationship with shared-bike utilization rate. In other words, bikes in those large companies were not used more efficiently than those in small companies. This uncovers a potential oversupplied and over-competing DBS market in Shanghai. Under such circumstances, increasing the fleet size is not helpful anymore in promoting system efficiency.

All findings broadly hold robust under models with different buffer sizes. However, we uncovered some modifiable area unit problems which may be the source of the variance in model performance. We found LUM is not significant under a smaller buffer size, which is reasonable as LUM may not reflect the actual degree of land use mix when the aggregation unit is too small. On the other hand, the increase of buffer size may cause the attenuation of some variables' significance due to the inclusion of noisy information. The variance in model goodness-of-fit suggested the need to test different buffer sizes to determine the optimal aggregation unit, instead of directly using the catchment area to aggregate the contextual environment. Further study can explore in more detail by considering individualized optimal buffer size at the independent variable level.

6. Conclusions, policy implications, and future research

This study assessed BnR activities using DBS in Shanghai city by leveraging large-scale DBS trip data. Findings suggested that station features, land use, socio-demographics, roadway designs, transportation facilities, and operator features near the metro stations all played important roles in affecting BnR behaviors. However, the overarching effects may come from DBS operators, who located too many shared bikes around metro stations near the city center while disregarding those located in the suburbs. Overall, this study proposed a comprehensive statistical framework to evaluate BnR performance in DBS-metro systems, estimate BnR demand of riding shared bikes, support shared bike relocation, and eventually help promote the efficiency and attractiveness of using DBS as a feeder mode of transit.

Several findings are worthy of attention in regulating DBS programs. First, although various built environment factors are incorporated in the models, it should be noted that large-scale changes in the built environment surrounding metro stations are unlikely to occur in developed countries, and thus most proposed strategies related to land-use change will rarely be practicable. However, land-use changes often occur in the context of the developing world, especially when the proposed land use plans are compatible with other planning goals such as transit-oriented development. On the other hand, although the built environment is difficult to modify, DBS operators can place a focus on the existing built environment when dispatching shared bikes, especially the positive factors such as degrees of mixed land use, the percentages of residential and public land, and the presence of colleges and shopping malls.

Second, the different relationships revealed by the four BnR metrics highlight the necessity of evaluating BnR from multiple perspectives. Operators should not only focus on the total number of trips but should also consider the utilization efficiency of bikes. When increasing the fleet size fails to lead to an increase in bike utilization rate, the oversupplied and over-competing market may be established. Meanwhile, local governments should attach more importance to the equality, accessibility, and convenience of BnR services particularly in suburban areas seeing sustained demand (Hu et al., 2021b; Ji et al., 2018; Mooney et al., 2019; Qiao et al., 2021).

Third, models constructed in this study help estimate the demand for shared bikes and identify whether the area is oversupplied or underserved, which is critical for DBS operators to set up an optimal management strategy. Specifically, at metro stations in urban cores where shared bikes are oversupplied and highly accessible, regulating parking is more important than providing bikes. Suggested procedures include estimating real cycling demand and circulating redundant bikes to underserved areas, assigning geographically differentiated bike rack quotas to DBS operators, charging users for illegal parking, and giving credit points to users for returning bikes to designated parking locations (Mooney et al., 2019; Tu et al., 2019). At metro stations in middle-density areas, such as suburban areas with high population density, where BnR demand is unmet and negative externalities resulting from the oversupply of dockless bikes are mitigated, cultivating BnR habit via adequate supply of shared bikes is a win-win strategy to all participators. At metro stations in low-density areas, DBS operators do not have the motivation to allocate bikes due to the lack of users. However, considering the equality of mobility services, local governments should tailor subsidies and policies to these underserved areas to maintain necessary connectivity. DBS operators should also develop more advanced ways to track bikes and prevent bikes from being lost and vandalized (Ji et al., 2017), or consider the integration with other shared mobility like car-sharing and bus systems.

Several limitations are recognized and deserve further research. First, variables used in our models are correlational and cannot prove causality. Second, all analyses were deduced at an aggregate level in the absence of available information at the individual (i.e. the DBS users) level; hence, conclusions should not be extrapolated to individuals considering the possibility of the ecological fallacy. Third, our data only represents the behavior of DBS users, which may render biases due to the underrepresentation of people riding their bikes or docked shared bikes to BnR. The method to identify BnR trips is also not perfectly accurate since the trip chain information is missing. Last, only one city is analyzed in this study and results may be region-specific. A verification for different scenarios is needed to test the generalizability of the above findings.

Author statement

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Declaration of Competing Interest

The Authors declare no conflict of interests.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jtrangeo.2021.103271.

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