Dockless bike-sharing as a feeder mode of metro commute? The role of the feeder-related built environment: Analytical framework and empirical evidence

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Abstract: The newly prevailing dockless bike-sharing system offers a decent solution to the first- and last-mile problem and connect trip origins/destinations and transit (mostly metro) stations. Few studies, however, have explored the effects of built environment characteristics on the integrated usage of dockless bike-sharing and the metro, especially in different conditions (e.g., access versus egress and morning peak versus evening peak) and using panel data. To fill the gap, this study proposes a *people–metro–bike–route–urban space* framework to describe the feeder-related built environment from the perspective of the feeder process. Using 3-day data of ofo bikes in Shenzhen, China, this study then develops multilevel negative binomial models that incorporate random effects and address the intracluster correlation attributed to the repeated measures to scrutinize the feeder-related built environment effects on the integrated usage. The findings are listed as follows: (1) The majority of access and egress integrated trips have a distance range of 500–2000 m and a duration range of 2.5–10 min; (2) Popular metro stations (with a large ridership) are positively related to the access integrated usage; (3) The number of available shared bikes and the length of bikeway in the catchment areas of the metro are positively related to the integrated usage under some scenarios; and (4) Mixed land use and a low proportion of office land use at the workplace side increase the integrated usage, whereas urban villages are places with few demands for the integrated usage. These findings are beneficial in developing a bike-friendly built environment that facilitates the seamless connection between dockless bike-sharing and the metro.

Keywords: dockless bike-sharing; built environment; feeder mode; metro; integration; public bicycle

1. Introduction

As a green travel mode, bike-sharing increases the share of sustainable mobility without emissions (Martens, 2007; Jin et al., 2018; Cao & Shen, 2019), offers personal health benefits by ramping up physical activities (Pucher et al., 2010; Leister et al., 2018), and extends the service catchment areas of public transit (Fishman et al., 2014; Lin et al., 2019). It has emerged as a mode of transport in a large number of contexts, such as Europe, Australia, and China (Shaheen et al., 2010; Soriguera & Jiménez-Meroño, 2020). Besides being a stand-alone travel mode, bike-sharing has an essential function: serving as a feeder mode of the metro (Shaheen et al., 2010; Zhao et al., 2019; Guo & He, 2020). The integration of bike-sharing and the metro can effectively solve the first- and last-mile problem (Griffin & Sener, 2016; Ji et al., 2017; Guo & He, 2020). Recently, along with the rapid expansion of bike-sharing, it has substantially grown in the past decade in many countries (e.g., China and Singapore). Integrating bike-sharing with the metro is persuasive, especially in high-density contexts (Wang & Liu, 2013; Lin et al., 2017; Ni & Chen, 2020). For instance, in Taipei, 95% of the leading origin–destination (O–D) pairs of YouBike use records were located near metro stations during weekdays (Lin et al., 2017).

As the largest bike-sharing market globally, China has seen unprecedented growth and expansion in bike-sharing, especially dockless bike-sharing (the new pattern of bike-sharing without fixed docking stations, also known as free-floating bike-sharing) since circa 2015. The number of dockless shared bikes (e.g., ofo and Mobike) has increased to 23 million in February 2018 in China (Gu et al., 2019). Dockless bike-sharing is more flexible to use than station-based (or dock-based) bike-sharing because it is not constrained by designated stations (Chen et al., 2018). The dockless bike-sharing system can enable cyclists to pick up and drop off bikes more freely than station-based bike-sharing (Guo & He, 2020). As such, this system provides a quicker and more flexible travel choice than station-based bike-sharing when connecting with the metro, particularly for riding bikes to (the access integrated usage) and from (the egress integrated usage) metro stations (Lu et al., 2018; Guo & He, 2020).

Infrastructural and economic policy measures, such as the provision of docking stations near metro entrances, have been implemented in various contexts to strengthen the integration of bike-sharing (mostly the station-based type) and the metro. However, the integrated usage level of bike-sharing and the metro is determined not only by the policy factors mentioned above but also by built environment features around metro stations, home/workplaces, and the route to/from stations. It is widely recognized that the built environment affects the travel behavior of bike-sharing and transit users (Cervero, 2002; Stewart & Moudon, 2014). However, most, though not all, of existing studies only focused on station-based bike-sharing (Ma et al., 2015; Zhao & Li, 2017; Ji et al., 2017, 2018; Eren & Uz, 2019). Limited studies have explored the built environment effects on the integrated usage of dockless bike-sharing and the metro (Wu et al., 2019; Guo & He, 2020). Comprehensive studies on the feeder-related (or feeder-process-related) built environment (i.e., related to origin/destination, transfer point of the station, and route to/from the station) have been sorely lacking.

To address the abovementioned issues, using 3-day data from a gigantic bike-sharing operator in Mainland China (i.e., ofo) and taking Shenzhen as a study area, this study aligns with the research needs for measuring the integrated usage of dockless bike-sharing and the metro and for exploring the impacts of built environment attributes on the integrated usage in different conditions by using multilevel negative binomial modeling. Notably, in contrast to prior bike-sharing behavioral studies relying on single-level models (Wu et al., 2019; Guo & He, 2020; Wang et al. 2020), this study introduces the multilevel modeling framework (Meng et al., 2020) to the studied problem for the better use of the repeated measures data (multi-period ridership). Additionally, in line with Wu et al. (2019) and Guo & He (2020), a fundamental assumption of this study is that making (starting or stopping) bike-sharing trips in areas in close proximity (e.g., 100 m) to metro stations can be considered as a bundle trip with the purpose of metro use. Given that the majority (approximately 57%) of the integrated usage occurs during two peak hours with the purpose of metro commute (Guo & He, 2020), this study scrutinizes the built environment effects on the integrated usage during peak hours and attempts to derive targeted policy and practical implications accordingly. This study can answer the following four questions: (1) What are the features of the integrated usage regarding the distance and duration of feeder trips? (2) Are the features different in different conditions (e.g., access versus egress and morning peak versus evening peak)? (3) How to measure the feeder-related built environment? (4) What are the impacts of feeder-related built environment attributes on the integrated usage?

This study makes five contributions: (1) proposing a novel *people–metro–bike–route–urban space* framework to describe the feeder-related built environment; (2) comparing the features of the integrated usage of dockless bike-sharing and the metro in different conditions; (3) investigating the contributory role of the built environment in shaping the use of dockless bike-sharing as a feeder mode of the metro; (4) introducing the multilevel modeling framework to the studied problem; and (5) discussing practical implications drawn from the empirical findings.

The remainder of this paper is organized as follows. Section 2 offers a review of the literature on the measurement and built environment correlates/determinants of the bike-sharing–metro integrated usage and policy measures promoting the integrated usage. Section 3 describes the study area, data, and measurement of the integrated usage. Section 4 proposes the *people–metro–bike–route–urban space* framework. Section 5 introduces the multilevel negative binomial model and variables. Section 6 displays the empirical findings. Section 7 concludes the paper, offers policy and practice implications, and summarizes research limitations.

2. Literature review

2.1. Measurement of bike-sharing–metro integration

The identification of (station-based and dockless) bike-sharing–metro trips is the first and foremost issue in understanding the integration itself and its determinants. Field questionnaire surveys are a commonly used approach (Zhao & Li, 2017). Ji et al. (2017) conducted questionnaire surveys in Nanjing and found that male commuters use bike-sharing more often to connect the metro than female counterparts. Yang et al. (2016) concluded that bike-sharing is a simpler and more efficient mode to feed the metro for suburban commuters than others by analyzing data collected from the survey instrument. Zhao & Li (2017) surveyed 36 metro stations in Beijing and interviewed over 700 transit users. They further identified the socioeconomic and built environment determinants of using bike-sharing (versus bus, car, and walking) as the transfer mode. Similar surveys have been applied in Beijing, Tokyo, and Taipei (Lin et al., 2018).

Another approach to identify (station-based and dockless) bike-sharing–metro trips is to analyze the smart card data that combine the records of bike-sharing and metro transactions. The bike-sharing–metro integrated usage can be identified into access and egress patterns by mining the transferring location and time (Ma et al., 2018a). However, the method only applies to station-based bike-sharing because using dockless bike-sharing does not rely on the smart card but involves smartphone applications.

The quantitative measurement of the dockless bike-sharing–metro integration has seldom been studied. Currently, no platform that simultaneously records dockless bike-sharing use and metro use exists. In other words, the symbiotic data of usage records of dockless bike-sharing (i.e., ofo and Mobike) and urban transit are inaccessible. Moreover, implementing questionnaire surveys is difficult and costly (Ma et al., 2018b). Furthermore, analyzing the dynamic variations of dockless bike-sharing–metro integration from temporal and spatial perspectives (as we do in this study) is difficult in view of the limited sample size and small spatial scope of survey data. Therefore, new data sources should be further explored when determining the dockless bike-sharing–metro integrated usage and describing the usage characteristics. Fortunately, the GPS device on dockless bike-sharing enables operators to locate and track the bikes under the support of real-time locational information. It also allows researchers to identify the integrated usage of mass real-time location data of dockless bike-sharing by analyzing the relative location with metro stations. Wu et al. (2019) made the first attempt and revealed the feasibility of using dockless bike-sharing location data to infer the bike-sharing–metro integration. Wang et al. (2020) and Guo & He (2020) followed their approach. As formerly noted, an underlying assumption of their approach is that making dockless bike-sharing trips in close proximity (e.g., 100 m) to metro stations can be considered a bundle trip with the purpose of metro use.

2.2. Built environment determinants of bike-sharing–metro integration

According to travel behavior theory, the spatial distribution of activities and the time constraint are determined by the built environment. Numerous empirical studies have demonstrated the built environment effects on the bike-sharing–transit (not necessarily metro) integration (Martin & Shaheen, 2014; Griffin & Sener, 2016). The investigated built environment features include distance to/from transit, land use, distribution of point of interests (POIs), urban design, presence of bicycle lanes, and other transportation facilities.

Transfer distance to/from the metro station is often deemed a decisive factor for transit users in deciding whether to opt for bike-sharing to connect metro stations or not (Ma et al., 2018a). It is exclusively affected by the spatial distribution of trip origins and metro stations. Generally, only in the case that the distance is moderate (e.g., 1-4 km in Beijing, see Zhao & Li, 2017) would metro takers choose bike-sharing. On the contrary, if the distance is too short, bike-sharing will likely be replaced by walking. On the other hand, if the distance is too long, motorized modes, such as the bus, taxi, and ridesourcing (e.g., Uber and Lyft) (Ke et al., 2017), are more advantageous because of the physical limitations of cyclists (Ma et al., 2018a; Yang et al., 2020).

The effect of population density remains highly mixed, even conflicting. In North American cities with low population density, people incline to use bike-sharing in suburban areas (Martin & Shaheen, 2014). By contrast, for East Asian modern cities (e.g., Singapore, Beijing, and Chengdu), the bike-sharing–metro integrated usage is likely concentrated in dense areas (Ji et al., 2018; Lin et al., 2018). Furthermore, population density is confirmed to be unrelated to the integrated usage in Taipei and Tokyo (Lin et al., 2018). On the other hand, the role of employment/job density in shaping the integrated usage is relatively consistent. As expected, areas with dense job distribution have a great attraction to bike-sharing–metro integrated usage because bike-sharing stations are likely to be located around metro stations to meet commuting demands (Ma et al., 2015).

The effects of land use on bike-sharing–metro integration have widely been identified. Ji et al. (2018) found that a large proportion of governmental, commercial, and industrial land use is significantly associated with the integrated usage and that bike-sharing–metro usage infrequently occurs around education land. Additionally, the impact of residential land use on the integrated usage is insignificant. Lin et al. (2018) revealed a positive linkage between mixed land use and the integrated usage in Taipei, Tokyo, and Beijing. Some POIs in metro catchment areas, such as leisure-, retail shopping-, food-related places, and hospitals, have insignificant impacts on the integration (Ji et al., 2017, 2018). However, many shopping malls around metro stations seem to discourage the use of bike-sharing from accessing the metro, while the public park around metro stations encourages the usage (Zhao & Li, 2017).

The impacts of urban roads (e.g., bicycle lanes, branch roads, main roads, and highways) on the bike-sharing–transit integrated usage have been verified as well. Zhao & Li (2017) revealed that the presence of exclusive bicycle lanes within metro catchment areas was unrelated to the probability of transferring via bike-sharing because exclusive, dedicated bicycle lanes are often occupied by cars and taxis, particularly during peak times in Beijing. Moreover, bike-sharing–metro integrated usage declines in places with many arterials and street intersections along the to-metro route (Lin et al., 2018). Another interesting finding is that the more bus stops around metro stations, the less bike-sharing–metro integrated usage. This outcome can be explained by the competition between the bus and bike-sharing in connecting the metro (Zhao & Li, 2017; Ji et al., 2018).

However, almost all of the studies above have used metro-station-based buffer zones as the analysis unit to describe built environment features. The radius of the buffer zones ranges typically from 300 m to 2 km. Some studies have used different buffer zones to extract various built environment features pertaining to land use, POIs, and transportation facilities. For instance, Zhao and Li (2017) measured transportation facilities and services within the buffer of 400 m and population, employment, and land use features within 1500 m from the metro station.

Built environment variables in these studies are classically categorized into three groups, namely land use, transportation facilities, and urban design (Handy et al., 2002). Nevertheless, the unique situation of the feeder process to or from the metro by bike-sharing is disregarded. Moreover, limited previous studies have concentrated on the linkage between dockless bike-sharing–metro integration and the built environment. More sophisticated studies are indispensable. Furthermore, the built environment effects on the integrated usage may vary between the access and egress patterns and between morning and evening times. This, however, is seldom captured by existing studies.

2.3. Policy measures promoting bike-sharing–transit integration

Operators, governments, and urban planners proposed many policies and strategies (e.g., the provision of docking stations near metro entrances, the extension of the bike-sharing service time, and the fare discount plan that combines bike-sharing membership and transit pass) to improve the integration of (station-based and dockless) bike-sharing and transit (mostly metro) (Shaheen et al., 2011). They can be roughly categorized into the following three groups: infrastructure measures by operators, promotional activities by operators, and planning strategies by governments and urban planners.

First, placing bike docking stations near transit station entrances and opportunities (e.g., homes, employment opportunities, shopping centers, activities centers) is a popular infrastructure measure to enable transit users to use bikes conveniently (Shaheen et al., 2011; Faghih-Imani & Eluru, 2016a, 2016b; Wang et al., 2016). In addition to this measure, adjusting the holding capacity of docking stations throughout the city is proposed to increase the fluidity of the bikes (Faghih-imani et al., 2014). Docking stations near metro entrances must be carefully considered. Furthermore, frequently rebalancing or adjusting bikes within their service catchment areas according to real-time demand is often adopted. Second, aside from infrastructure policies, promotional activities, such as financial incentives (fare integration and charge reduction/exemption) for jointly using the metro and bike-sharing (Ahillen et al., 2016), also contribute to the bike-sharing–metro integration. Last, to strengthen the bike-sharing–transit integration, governments and urban planners have proposed several planning strategies, such as offering dedicated bike lanes on existing roadways and improving the parking space near metro stations (Jia et al., 2018).

3. Measurement of dockless bike-sharing and the metro

Generally, the integration of the bicycle (i.e., private bicycle, rental bicycle, and station-based/dockless bike-sharing) and the metro has four patterns (Krizek & Stonebraker, 2011; Singleton & Clifton, 2014).

1. Bicycle-and-transit (cycling to the transit station or access integration);
2. Transit-and-bicycle (cycling from the transit station or egress integration);
3. Bicycle-transit-bicycle (the combination of Patterns 1 and 2);
4. Bicycle-bring on transit-bicycle (the combination of Patterns 1 and 2 and bringing the bicycle aboard).

Since the worldwide prosperity of bike-sharing in the 2000s, particularly after Paris's Vélib program in 2007, bike-sharing has gradually become a popular feeder mode of transit. The integration of bike-sharing (including both station-based and dockless types) and the metro involves Patterns 1, 2, and 3.

3.1. Study area

Bordering Hong Kong, Shenzhen is a famous international metropolis located in Guangdong Province, South China. As of 2018, Shenzhen had a population of 13.02 million and an area of 1997 km^2, and its GDP was 2469.1 billion RMB (Top 3 in Mainland China) (Bao & Lu, 2020). Before July 2010, Shenzhen was divided into the special economic zone (SEZ) (i.e., Futian, Luohu, Nanshan, and Yantian districts) and non-SEZ. The administrative segmentation has been canceled after 2010, and the SEZ has been extended to the whole city. Nanshan, Futian, and Luohu districts in the original SEZ are treated as the downtown by the city government, whereas other districts are classified into suburban areas (Fig. 1). However, some suburban areas close to the downtown, such as Bao'an South, Longhua South, and Longgang West, have experienced rapid development over the last ten years. Numerous residential and commercial properties have been constructed in these areas. Many residents live in these areas and work downtown, thereby clustering various high-tech and finance companies, commercial facilities, governments, and entertainment activities, with an acceptable commuting time due to the relatively low housing rent. This phenomenon leads to spatial commuting tides across the city on weekdays. Furthermore, suburban areas that are far from downtown are still covered with a large number of manufacturing industries. The self-employed economy of the retail and catering industries are prosperous to provide daily-life services for people residing in these areas, and most of them are migrants working in industrial factories. Therefore, the built environment attributes are quite different in the downtown and suburban areas .

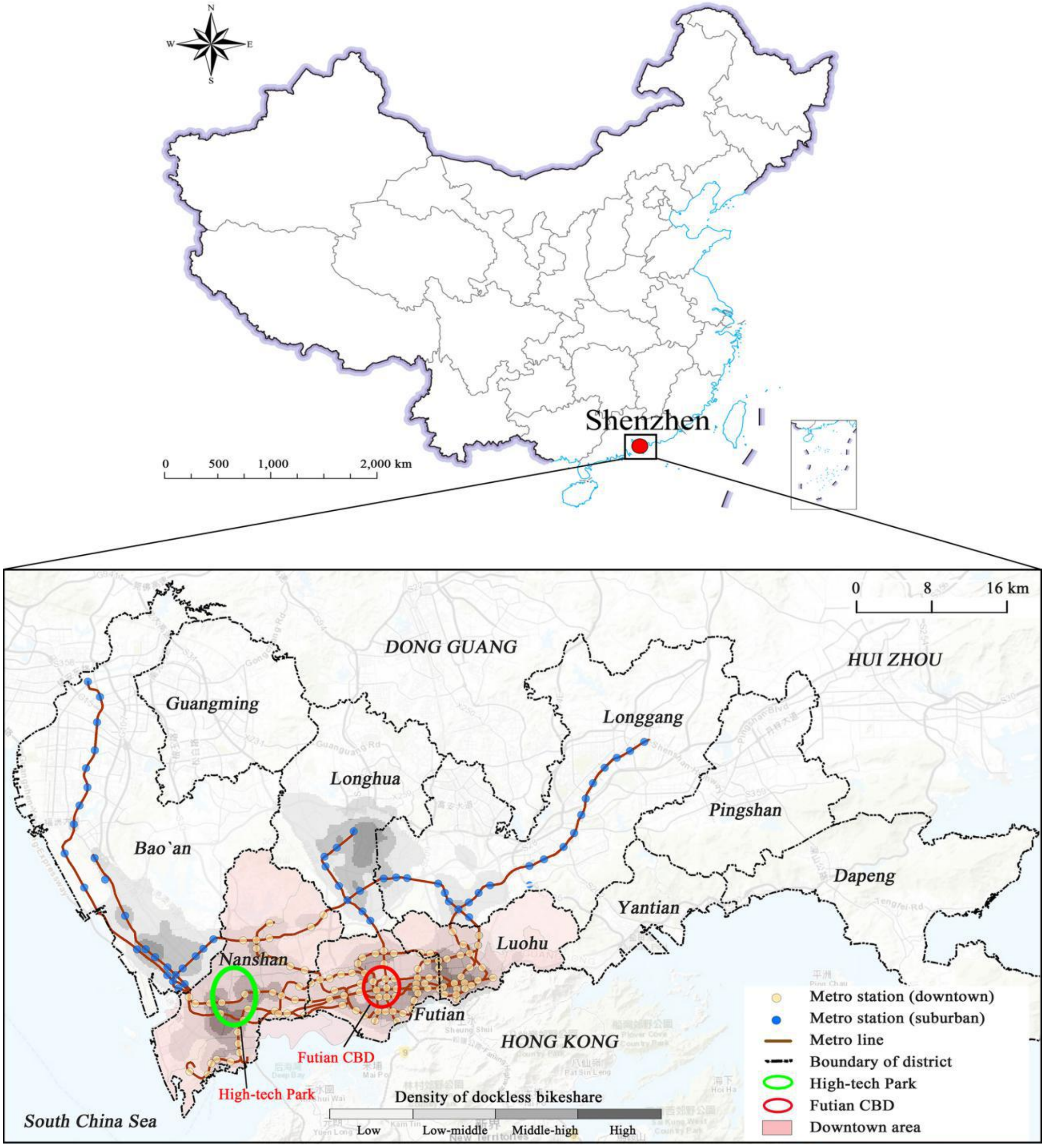

Fig. 1. Study area and distribution of dockless bike-sharing

In Shenzhen, the metro is a popular travel mode, constituting over 40% of residents' trips. The daily metro ridership of Shenzhen in 2018 was 5.14 million. Until the end of 2018, 8 metro lines totaling 296.7 km and 167 metro stations were available, and 2/3 of the stations were located in the downtown. However, stations with a large ridership, such as Shenzhen North Railway station and Wuhe station, were usually situated in suburban areas. Several metro lines that integrate the downtown and suburban areas are currently under construction.

Along with the rapid expansion of the metro system, the dockless bike-sharing system has flourishingly appeared and rapidly advanced. In September 2016, Shenzhen launched its first dockless bike-sharing program (i.e., Mobike). As of the early of 2019, approximately 480,000 dockless shared bikes have been utilized, and the associated membership was 26.47 million (Shenzhen Transportation Bureau, 2019). As shown in Fig. 1, the dense areas with a large number of bike-sharing include the south of Longhua and Bao'an districts (suburban areas) and Nanshan district. However, the use of dockless bike-sharing in remote regions is minimal.

3.2. Data

In this study, parking location data of ofo bikes were used to identify the dockless bike-sharing–metro integrated usage (Wu et al., 2019; Guo & He, 2020). The 24-hour location data of bikes were crawled from the ofo online app (interval time = 3–5 min). Bicycle ID (mixed with number and letters), location (longitude and latitude with six decimal places), and time (accurate to the second) of parking bikes were included in the data. However, the data were static, only indicating the location of each dockless bike-sharing (identified by unique IDs) at the crawling time rather than reflecting the dynamic route of bike-sharing trips. Within each interval time, approximately 220,000 pieces of locational information were collected across Shenzhen (detailed in Section 5).

Three-day ofo bike data were collected for analysis. The three consecutive weekdays were September 26 (Tuesday), 27 (Wednesday), and 28 (Thursday). The average temperature ranged between 27 °C and 32 °C, and the weather condition (i.e., sunny and cloudy) was reasonably suitable for cycling.

The analysis of the three-day data is expected to address potential day-to-day variances. According to some empirical studies, the characteristics of daily dockless bike-sharing usage were fairly consistent across five weekdays (Yang et al., 2019; Guo & He, 2020). As such, it is feasible to assume that the selected 3-day data are representative of the dockless bike-sharing use on weekdays (Guo & He, 2020).

3.3. Measurement of the integration: a big data-based approach

In line with Wu et al. (2019) and Guo & He (2020), the use of dockless bike-sharing for metro access and egress is measured by the *counts of the valid use of shared bikes in the 100 m buffer of metro entrances* (Fig. 2). Moreover, we also conducted a self-administrated face-to-face questionnaire survey in Shenzhen on weekdays from October to November in 2019. In this survey, we randomly selected 22 metro stations in Shenzhen and received 1,702 questionnaires, 1,167 of which were valid. The results show that most (> 95%) of the respondents park their shared bikes (first-mile) or use the bike-sharing service (last-mile) in the immediately adjacent area (100 m) of a metro station. This observation also justifies the choice of the distance threshold. The 100 m buffer of metro entrances is applied as the most likely parking area around metro stations.

Following Wu et al. (2019) and Guo & He (2020), the integrated usage is identified in the following three steps (Fig. 3): 1) identification of the valid movement; 2) establishment of the parking area for bicycle in close proximity to metro stations; and 3) distinguishing of the access and egress integrated usage.

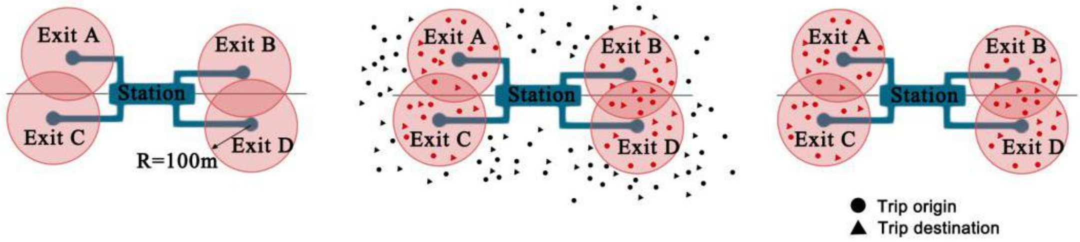

Fig. 2. Identifying the integrated usage by a big data approach

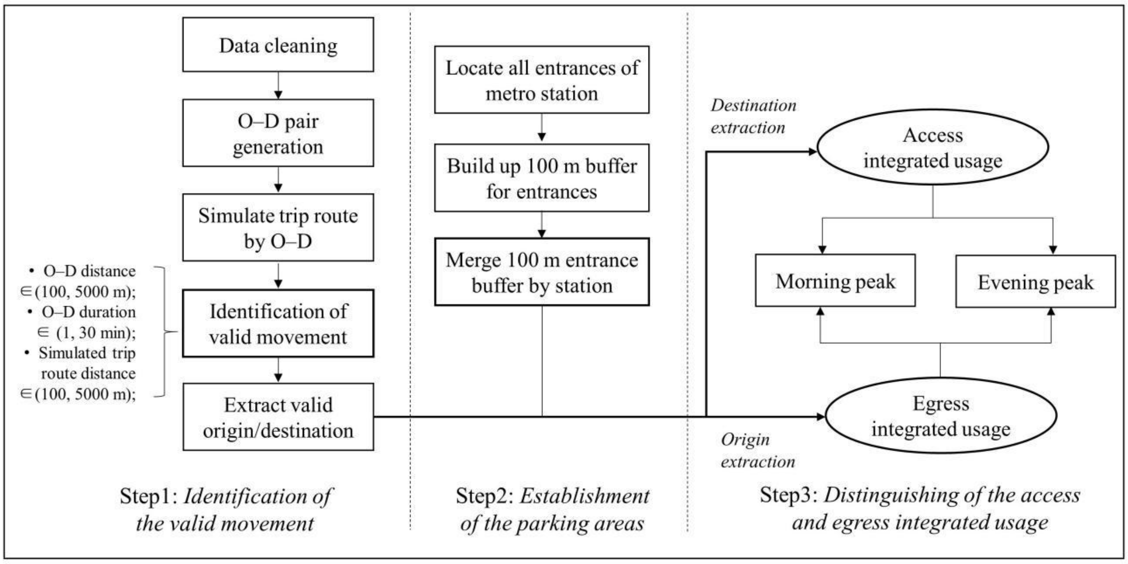

Fig. 3. Complete process of identifying the integrated usage

- *Step 1: Identification of the valid movement*

Processing the raw data is essential. In the crawled raw dataset of the parking location of ofo bikes, the interval time of crawling is approximately 3 min. As such, the locational information of a unique bike can be recorded many times repeatedly in a short period. The bikes that did not move throughout the whole day (24 hours) were deemed broken and thus excluded from the subsequent analysis. Consequently, the left bikes are the ones with movements. Moreover, the duplicated records of these moved or used bikes were discarded. Then, O–D analysis for each trip is conducted. However, the O–D pair is unconvincing as evidence for identifying the valid movement. Route analysis is then performed under the support of API service of AMAP (an online map company, similar to Google Map) based on O–D pairs. The trip distance and time are calculated under the mode of cycling when route analysis is conducted.

The dockless bike-sharing use is deemed valid if it meets three criteria simultaneously. First, the Euclidean distance of the O–D pair is typically 100 m - 5 km. Second, the simulated trip distance is 100 m - 5 km. Third, movements with possible abnormal durations (> 30 min) should be excluded (Wu et al., 2019; Yang et al., 2019; Wang et al., 2020).

- *Step 2: Establishment of the parking area for each metro station*

Among all valid movements, isolating their integrated usage requires distinguishing whether the origin/destination of the movement is from/to metro stations. In this step, the buffer of each metro station entry is applied to estimate the most likely parking area around metro stations.

Entries of each metro station are initially geo-coded in the GIS system. (All the metro stations in Shenzhen have over two entries.) Then, the 100 m buffer is generated for each entry, similar to Wu et al. (2019).

- *Step 3: Distinguishing of the access and egress integrated usage*

Two types of the integrated trips by dockless bike-sharing can be identified by checking the position of origin and destination of the route: (1) Access integrated usage: the trip with a destination located in the entry buffer; (2) Egress integrated usage: the trip with an origin located in the entry buffer. Afterward, the access and egress integrated usage in the morning (7:00–9:00 am) and evening (5:30–7:30 pm) peaks are extracted.

It is essential to assume that dockless bike-sharing users who drop off a bike in close proximity to metro entries (i.e., access integrated usage) have a purpose of taking the metro, while the dockless bike-sharing users who pick up a bike in close proximity to metro entries (i.e., egress integrated usage) are those who have already finished their metro trips. This assumption is also made by Wu et al. (2019) and Guo & He (2020).

4. Analytical framework: feeder-related built environment

It is commonly known that the built environment is a multi-dimensional construct, which is highly difficult to measure. Many researchers such as Cervero and Kockelman (1997) and Ewing and Cervero (2010) put forward meaningful modeling approaches of the built environment (the "3Ds" or "5Ds" framework). Their approaches can effectively represent the built environment at the neighborhood level (e.g., within a 400 m, 800 m, or 1 km buffer zone of a location, such as a house) at an acceptable level of accuracy. They, however, cannot well describe the built environment specific to the dockless bike-sharing–metro integration and thus cannot be directly applied to this study. In other words, to our knowledge, there is no analytical framework for the description of the feeder-related built environment (which is evidently unique) in existing literature. Therefore, this study attempts to fill the research gap.

The feeder process of the dockless bike-sharing–metro integration (Fig. 4) is considered in the analytical framework (Fig. 5). Commonly, the process of metro feeder trips by bike-sharing consists of five components, namely *People, Metro, Bike, Route, and (Contextual) urban space.* Factors associated with *Bike* reflect the supply of dockless bike-sharing bikes, which are arguably important for the integrated usage. Factors related to *People* and *Metro* are connected with the demand for feeder trips internally. By contrast, factors pertinent to *Route* and *Urban space* may affect the integrated usage externally. All in all, built environment attributes related to these five components are expected to affect the dockless bike-sharing–metro integration.

Moreover, the impacts of built environment features (e.g., job density) may vary across integration mode (access or egress) and time of day (morning peak or evening peak). Therefore, according to the conditions of bike-sharing used as an access/egress feeder means at two peak times, we separate the integrated usage into four scenarios: access integration at the morning peak (MA), egress integration at the morning peak (ME), access integration at the evening peak (EA), and egress integration at the evening peak (EE).

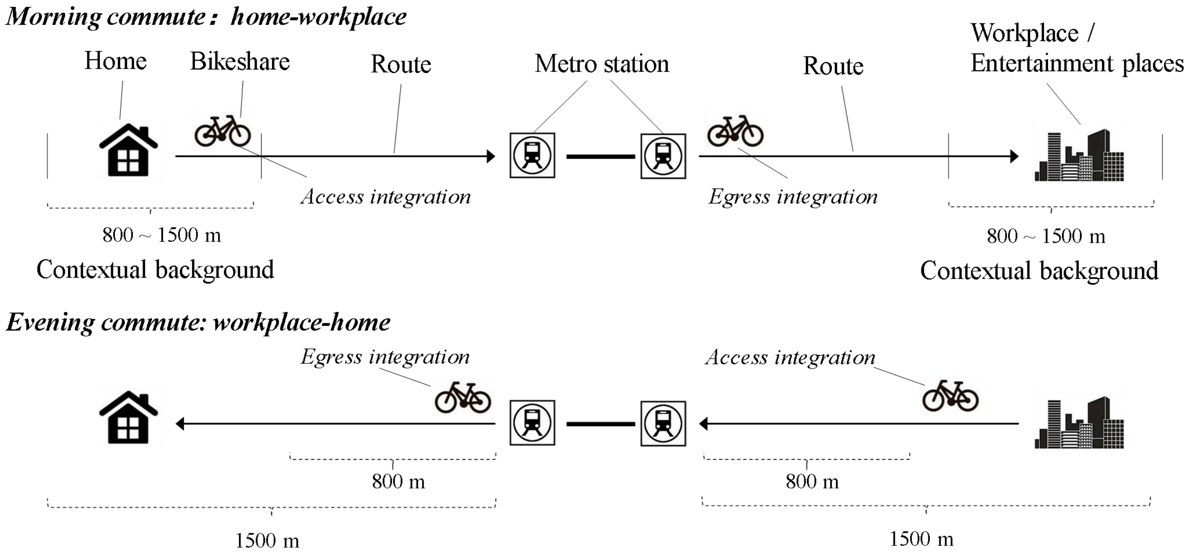

Fig. 4. Feeder process of connecting the metro station by bike-sharing

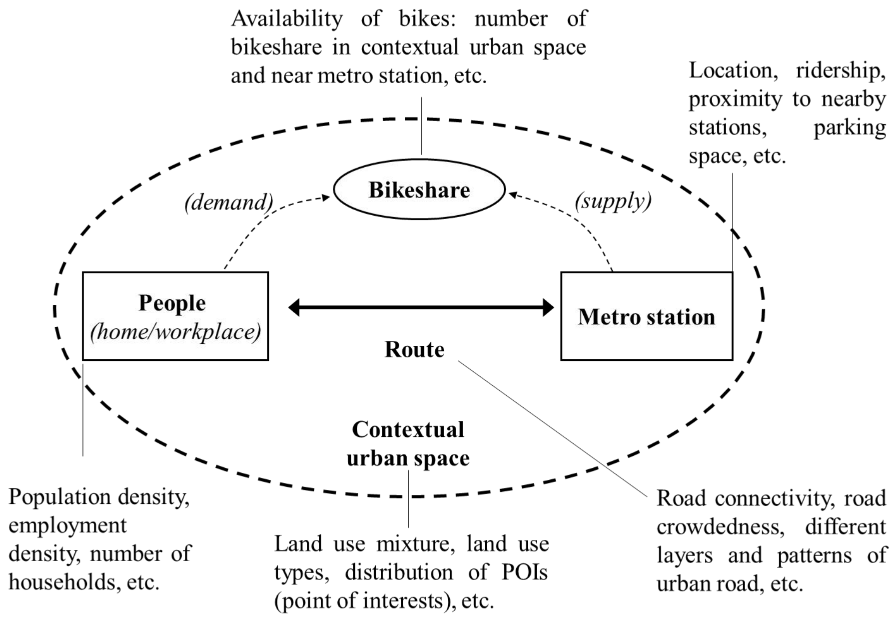

Fig. 5. The feeder-related built environment for bike-sharing–metro integration

As Fig. 4 presents, the area within the 800–1500 m radius of metro stations is the major attractive urban space that generates a large number of potential demands for the bike-sharing–metro integrated usage. The spatial range herein follows the Chinese urban context because most pedestrians in dense Chinese cities (e.g., Shanghai and Shenzhen) tend to walk for a short distance to connect the metro. For example, 80% of pedestrians walk less than 1 km in Beijing (Zhao & Li, 2017). As a comparison, the appropriate cycling distance for connecting metro stations can range from 800 to 1500 m (Pan et al., 2010). Hence, bike-sharing can be more competitive than walking as a feeder mode of the metro when transfer distance falls in the range of 800–1500 m. Therefore, the area with a spatial range of 800–1500 m is set as the contextual background. The number of residents, households, employment opportunities, activity-related places, and land use can affect the integrated usage. Thus, the built environment within 800–1500 m is considered to be the contextual background.

Furthermore, the availability of shared bikes in the buffer (800–1500 m) and the metro-adjacent area affect transit users' propensity to opt for bike-sharing.

Route conditions (e.g., the presence of bicycle lanes and the number of road street intersections along the feeder route) of feeder trips to/from metro stations may affect the bike-sharing–metro integration.

Another essential factor that potentially influences the integrated usage is the metro station itself. For instance, sufficient parking space adjacent to station entries helps accommodate many transit users who ride bike-sharing to or from stations. Moreover, more metro stations nearby may decrease the access/egress distance, thereby increasing the possibility of walking to stations.

5. Methodology

5.1. Multilevel negative binomial regression model

The dependent variable is the integrated usage, which is measured by the counts of access or egress trips (a non-negative integer), so count data models are needed. The Poisson and the negative binomial regression models are two techniques to analyze the count data (Xu et al., 2019). However, the latter outperforms the former if overdispersion occurs because it does not restrict the variance to be equal to the mean (Cameron & Trivedi, 1988). It has been extensively used in travel behavior research (Handy et al., 2006; Forsyth & Oakes, 2015).

In contrast to prior bike-sharing studies relying on single-level models (Wu et al., 2019; Guo & He, 2020; Wang et al. 2020), the multilevel (more specifically, two-level random-intercept) negative binomial regression model is used to analyze our panel count data (3 observations for each station area) because it can incorporate random effects and address the intracluster correlation attributed to the repeated measures (Meng et al., 2019). The two-level random-intercept negative binomial regression model, which incorporate latent variable ζ_{ij} and random effects $\mathbf{u_j}$, can be expressed as follows:

$$y_{ij} \mid \zeta_{ij} \sim \text{Poisson}(\zeta_{ij})$$

$$\zeta_{ij} \mid \mathbf{u_j} \sim \text{Gamma}(\frac{1}{\alpha}, \frac{1}{1+\alpha\mu_{ij}})$$

$$\mathbf{u_j} \sim \text{N}(\mathbf{0}, \mathbf{\Sigma})$$

$$\Pr\left(y_{ij} = y \mid \mathbf{u_j}\right) = \frac{\Gamma(y+\frac{1}{\alpha})}{\Gamma\left(y+1\right)\Gamma(\frac{1}{\alpha})}\left(\frac{1}{1+\alpha\mu_{ij}}\right)^{\frac{1}{\alpha}}\left(\frac{\alpha\mu_{ij}}{1+\alpha\mu_{ij}}\right)^{y}$$

$$\mu_{ij} = E(y_{ij} \mid \mathbf{x_{ij}}, \mathbf{u_j}) = \exp(\mathbf{x_{ij}\beta} + \mathbf{u_j}) = \exp(\mathbf{x_{ij}\beta}) \times \exp(\mathbf{u_j}),$$

where the bold type denotes a matrix or a vector, y_{ij} is the count variable of the *i*th observation (*i* = 1, 2, 3) from cluster *j* (*j* = 1, ..., 159), $\mathbf{\Sigma}$ is a variance matrix that captures the random effects, $\Pr\left(y_{ij} = y \mid \mathbf{u}_j\right)$ is the probability that random response y_{ij} takes the value of *y* conditional on random effects $\mathbf{u_j}$, $\mathbf{x_{ij}}$ is a vector of the fixed-effects covariates, $\boldsymbol{\beta}$ is a vector of coefficients of the covariates, α is a positive constant, and μ_{ij} is the expectation of y_{ij} conditional on $\mathbf{x_{ij}}$ and $\mathbf{u_j}$.

5.2. Variables

Table 1 shows the definitions and descriptive statistics of the dependent and independent variables. As formerly mentioned, the dependent variables include access and egress integration at morning and evening peaks (i.e., MA, ME, EA, and EE), measured by the counts of the usage. As a comparison, a dependent variable of total integrated usage during peak times measured by the sum of MA, ME, EA, and EE is created. Table 1 shows that the average level of the access integrated usage at the morning peak is around 44% more than that at the evening peak. Meanwhile, egress integrated usage in the morning and evening peaks are almost similar. Figs. 6 and 7 are the histograms of the five dependent variables.

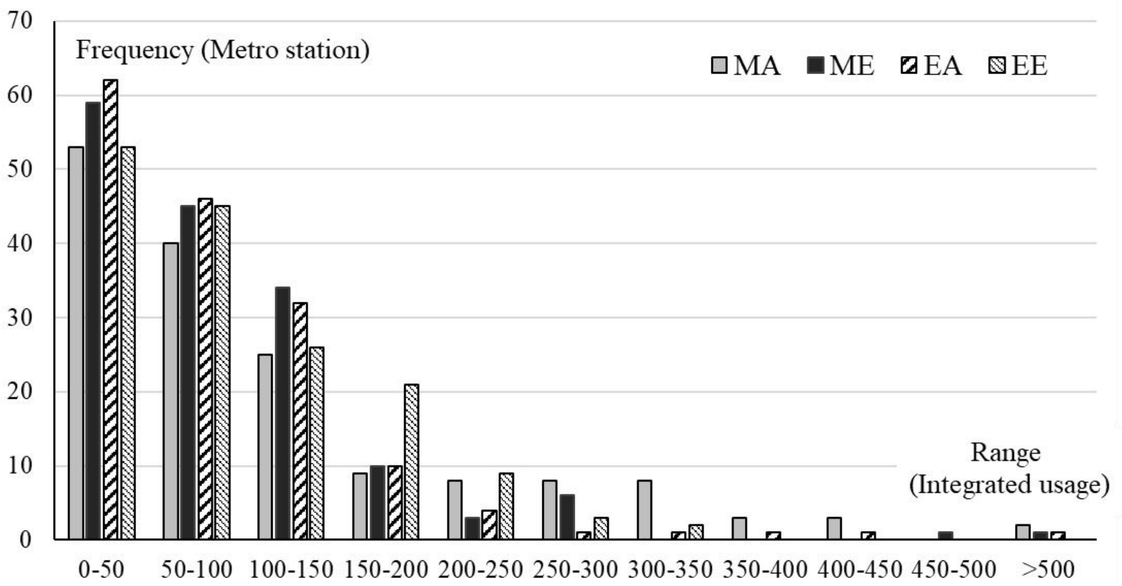

Fig. 6. Histogram of the access and egress integrated usage at the morning and evening peaks (MA, ME, EA, and EE)

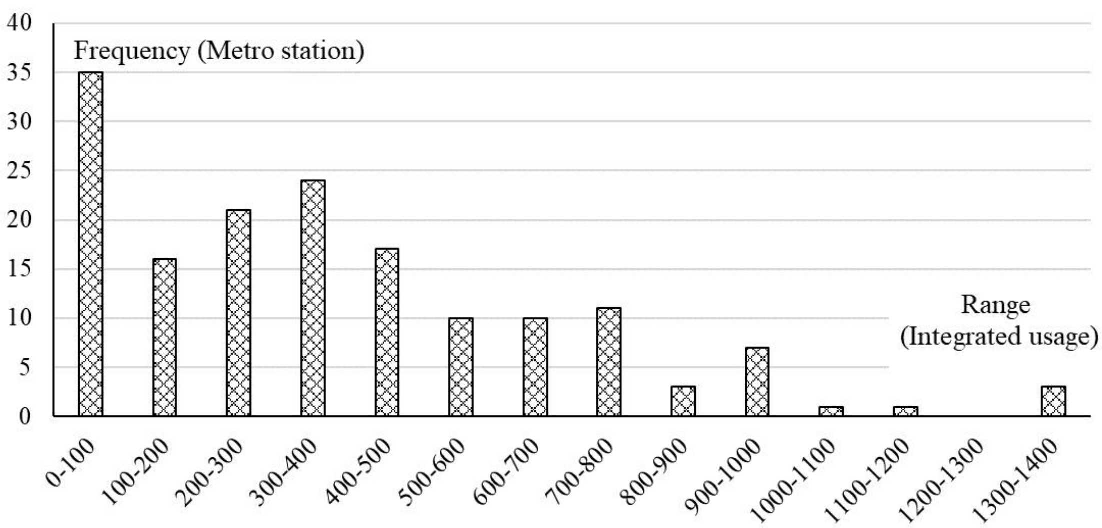

Fig. 7. Histogram of the total integrated usage

As for independent variables used in the study, following our proposed framework, built environment variables are categorized into five dimensions and measured as follows.

People: Population density and employment density are used to measure the potential demand for the integrated usage within the 800–1500 m buffer zone of the metro station. The data are calculated based on information on the traffic analysis zone (TAZ) in Shenzhen.

Metro station: Dummy variables are set to indicate the location of the metro station (downtown or suburban). As Table 1 shows, around 65% of metro stations are concentrated in downtown areas, whereas the other 35% are located in suburban areas. Ridership of the metro station is also considered because a higher ridership of a station is related to more bike-sharing users. The distance from a specific metro station to the nearest one is measured in the GIS framework. It is supposed that close proximity to other metro stations may reduce their integrated usage level.

Bike: The supply of dockless bike-sharing is assumed to facilitate the use of bike-sharing for reaching or leaving from metro stations. The number of ofo bikes within the 100 m buffer of metro entrances for egress and the number of ofo bikes in the 800–1500 m buffer for access are considered (see Fig. 4).

Route: The characteristics of road facilities, such as the length of bikeway/branch/main/highway road and the number of intersections in the 1500 m buffer of metro stations, are considered. The contributory role of the characteristics has frequently been pointed out in previous studies on the use of general bicycles (including but not limited to dockless bike-sharing). Bikeway often contributes to a high willingness to cycle by providing cyclists with a safe pathway to travel (Akar & Clifton, 2009; El-Assi et al., 2017). Branch road is expected to be positively associated with cycling, whereas the major road (or main road) and highway might have adverse effects (Lin et al., 2018). In addition, road intersection often negatively affects the use of bike-sharing (Lin et al., 2018).

(Contextual) urban space: Land use in metro catchment areas is considered in the proposed framework. Variables related to land use mix, percentage of commercial, office, urban community, and urban village land use are included. The entropy of ten land use types is applied to measure the land use mix with a possible positive effect on the integrated usage (Zhang et al., 2017). Commercial and office land use is likely to be correlated with working purposes. Meanwhile, the urban community and the urban village (*cheng zhong cun*, village-in-the-city) are typical residential land use in Shenzhen. Particularly, the urban village is located inside the city and provides relatively cheap accommodation to rural migrants and white-collar workers (Wu, 2009).

Notably, 8 out of 167 metro stations[1] are excluded because no bikes are distributed in these stations, and the other 159 stations are used in the subsequent analysis. As each station has three observations, the total number of observations is 477 (= 159 × 3).

[1] Fulin station is still out of operation even though it has been well built up, resulting in no integrated usage; Bitou, Hongshuwan South, Shenwan, and Tanglang stations are heavily surrounded by commercial properties under construction, and therefore, no integrated usage is found at these stations; and entries to the other three stations are located either adjacent to the airport (i.e., Airport and Airport North stations) or in a park (i.e., Shenzhen Bay Park station), where no integrated usage exists during peak hours (Guo & He, 2020).

Table 1 Definition and descriptive statistics of the variables (N=477)

Variables	Description	Mean	Std.	Min	Max
Dependent variables					
Morning access (MA)	Access integrated usage of the metro station at the morning peak	117.12	114.90	0	558
Morning egress (ME)	Egress integrated usage of the metro station at the morning peak	86.00	80.55	0	523
Evening access (EA)	Access integrated usage of the metro station at the evening peak	81.48	79.11	0	559
Evening egress (EE)	Egress integrated usage of the metro station at the evening peak	91.30	74.03	0	333
Total integration	Sum of MA, ME, EA, and EE	375.91	306.61	0	1401
Independent variables					
People					
Population	Number of people in the 800–1500 m circle buffer of the station (ten thousands/km^2)	27.50	14.28	3.07	59.15
Employment	Number of jobs in the 800–1500 m circle buffer of the station (ten thousands/km^2)	16.51	11.49	2.07	56.90
Metro					
Suburban	Dummy variable, 1 if the station is located in the suburban areas and 0 otherwise for a downtown location	64.78% downtown, 35.22% suburban			
Ridership	Daily ridership of the station during February 2018 (ten thousands)	2.72	2.26	0.08	15.95
Distance to the station	Distance to the closest metro station (km)	0.96	0.41	0.38	3.07
Bike					
Bike availability (MA)	Number of available bikes in the 800–1500 m buffer of the station (for access usage) at the morning peak	1490.27	1035.22	2	5636
Bike availability (ME)	Number of available bikes in the 100 m buffer of the station (for egress usage) at the morning peak	96.17	85.32	0	396
Bike availability (EA)	Number of available bikes in the 800–1500 m buffer of the station (for access usage) at the evening peak	1740.83	1201.62	3	5126
Bike availability (EE)	Number of available bikes in the 100 m buffer of the station (for egress usage) at the evening peak	91.92	71.32	0	318
Route (road)					
Bikeway	Length of bikeway in the 1500 m buffer of the station (km)	18.89	8.25	1.86	43.26
Branch road	Length of branch road in the 1500 m buffer of the station (km)	27.10	11.04	5.18	59.12
Main road	Length of main road in the 1500 m buffer of the station (km)	30.51	11.45	2.45	58.78

Highway	Length of highway (express road) in the 1500 m buffer of the station (km)	4.76	4.09	0	18.79
Intersection	Number of intersections in the 1500 m buffer of the station (hundreds)	377.17	163.78	82	895
Urban space (land use)					
Land use mix	Entropy of ten land use patterns in the 800–1500 m buffer of the station	0.70	0.06	0.48	0.81
Commercial	Percentage of commercial land use in the 800–1500 m buffer of the station (%)	0.03	0.02	0.0004	0.12
Office	Percentage of office land use in the 800–1500 m buffer of the station (%)	0.02	0.02	0	0.09
Urban community	Percentage of urban community land use in the 800–1500 m buffer of the station (%)	0.18	0.08	0.0027	0.36
Urban village	Percentage of urban village land use in the 800–1500 m buffer of the station (%)	0.06	0.06	0	0.26

6. Empirical results

6.1. Description of the integrated usage: trip distance and duration

The trip route is simulated by API service in AMAP using the O–D pair information. The results of the simulation include a route trajectory and its distance and duration. Table 2 shows that access and egress integrated usage (at morning and evening peaks) involved a similar trip distance (around 1,200 m) and trip duration (about 4.80 min). There are few variances among four scenarios of the integrated usage in terms of trip characteristics.

More specifically, about 40% of the integrated usage involved the duration of 2.5–5 min, followed by 5–10 min (approximately 28%). Very few transit users (less than 2%) had a first- and last-mile time longer than 15 min. Meanwhile, almost 33%–37% of the integrated usage involved a distance of 500–1000 m, which accounts for the largest share. 1000–1500 m was the second-largest distance range for transit users to tolerate for feeder trips by dockless bike-sharing. However, the integrated usage will decrease if the transfer distance increases, particularly beyond 1500 m.

Table 2 Trip duration and distance of the integrated usage simulated by AMAP (three-day records)

Trip duration	MA		ME		EA		EE	
	Counts	Ratio	Counts	Ratio	Counts	Ratio	Counts	Ratio
Less than 2.5 min	12,315	22.26%	9199	22.44%	9480	24.52%	10,415	24.70%
2.5–5 min	23,773	42.98%	17,258	42.09%	15,379	39.78%	16,098	38.17%
5–10 min	15,759	28.49%	11,525	28.11%	10,685	27.64%	12,288	29.14%
10–15 min	2655	4.80%	2343	5.71%	2385	6.17%	2608	6.18%
Over 15 min	813	1.47%	677	1.65%	728	1.88%	762	1.81%
Average (min)	4.72		4.82		4.81		4.84	
Trip distance								
Less than 500 m	7974	13.48%	5831	14.22%	6291	16.27%	6981	16.55%
500–1000 m	20,505	37.07%	14,603	35.62%	13,218	34.19%	14,067	33.36%
1000–1500 m	14,053	25.41%	10,193	24.86%	9040	23.39%	9705	23.01%
1500–2000 m	6634	11.99%	4724	11.52%	4585	11.86%	5389	12.78%
2000–3000 m	4693	8.48%	3913	9.54%	3746	9.69%	4090	9.70%
Over 3000 m	1975	3.57%	1738	4.24%	1777	4.60%	1939	4.60%
Average (m)	1178.99		1204.79		1204.21		1210.21	

6.2. Modeling results

Before constructing regression models, the multicollinearity (or non-independence of predictors) needs to be examined. According to the results of pair-wise correlation analysis, two variables, namely *Employment density* and *Intersection*, were excluded to avoid the multicollinearity problem. We developed four separate models to explore the built environment effects on the integrated usage under four scenarios and estimated a model for the total integrated usage. Table 3 reveals the multilevel negative binomial modeling outcomes.

Table 3 Results of the multilevel negative binomial regression models

Variable	Morning access (MA)		Morning egress (ME)		Evening access (EA)		Evening egress (EE)		Total integration	
	Coefficient	*z*-Stat.	Coefficient	*z*-Stat.	Coefficient	*z*-Stat.	Coefficient	*t*-Stat.	Coefficient	*z*-Stat.
People										
Population density	0.252*	1.68	0.275**	2.49	-0.038	-0.24	0.352***	3.16	0.060	0.39
Metro										
Suburban	0.202	1.28	-0.126	-1.14	-0.097	-0.65	0.221**	1.96	0.117	0.78
Ridership	0.205**	2.00	-0.061	-0.82	0.248***	2.63	-0.017	-0.23	0.182*	1.86
Distance to the station	-0.250*	-1.93	-0.228**	-2.48	-0.266**	-2.20	-0.273***	-2.97	-0.291**	-2.36
Bike										
Bike-sharing availability	1.033***	6.80	1.056***	13.54	1.124***	5.99	1.048***	11.86	1.322***	8.02
Route (road)										
Bikeway	0.213	1.46	0.168	1.64	0.286**	2.09	0.235**	2.27	0.221*	1.69
Branch road	-0.039	-0.32	0.035	0.41	-0.097	-0.85	0.009	0.10	-0.072	-0.62
Main road	-0.163	-0.91	-0.142	-1.14	-0.075	-0.45	-0.234*	-1.85	-0.237	-1.40
Highway	0.039	0.34	-0.050	-0.62	0.072	0.67	-0.046	-0.57	0.044	0.41
Urban space (land use)										
Land use mix	0.226**	2.03	0.166**	2.11	0.206**	1.98	0.164**	2.06	0.174*	1.64
Commercial	0.105	1.04	0.098	1.39	0.113	1.21	0.142**	1.99	0.127	1.33
Office	-0.473***	-3.19	0.042	0.41	-0.395***	2.76	-0.184*	-1.80	-0.463***	-3.24
Urban community	-0.009	-0.07	-0.195**	-2.26	-0.219*	-1.90	0.060	0.69	-0.168	-1.43
Urban village	-0.436***	-2.78	-0.401***	-3.62	-0.428***	-2.90	-0.460***	-4.11	-0.435***	-2.92
Constant	3.989***	43.99	3.804***	59.34	3.683***	43.29	3.870***	59.83	5.233***	60.73
$\log \alpha$	0.001	1.56	<0.001	<0.001	0.011***	5.27	0.007***	4.52	0.002***	4.75
Log-likelihood		-2053.310		-1913.283		-2027.664		-2031.835		-2523.986

Note: *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level.

6.2.1. The role of *people*

Population density is positively correlated with the integrated usage in MA, ME, and EE models. According to previous studies, population density's role in shaping the integrated usage remains highly inconclusive (Ji et al., 2018; Guo & He, 2020). The uncertainty of their effects could be related to the distinct characteristics of the urban context. For example, low population density in the US cities' suburban areas seems to induce the demand for the integrated usage, while the integrated usage tends to occur in dense areas in some Chinese cities (Martin & Shaheen, 2014; Lin et al., 2018). Another possible explanation is the nonlinear effect of density on travel behavior, which has recently attracted much attention in the urban transportation field but this study fails to capture (Choi, 2018; Tao et al., 2020). There may be a population density threshold that works on the integrated usage appropriately, and such a threshold varies among different urban contexts.

6.2.2 The role of *metro*

The location of the metro station likely affects the integrated usage. Suburban areas usually have more egress usage in the evening peak time. This is reasonable because many metro commuters live in suburban areas but work downtown, thereby generating high demands for back-home egress trips by dockless bike-sharing in the evening. Moreover, metro ridership is observed to have positive effects in access models but not egress models.

6.2.3. The role of *bike*

A consistently positive impact of bike-sharing availability occurs on all the five kinds of the integrated usage. As for the access integrated usage starting from home or workplaces, many shared bikes nearby (within the 800–1500 m buffer) will raise the possibility of choosing dockless bike-sharing as the feeder mode. A large number implies abundant opportunities, thereby decreasing users' searching time and increasing transit riders' willingness to choose bike-sharing in the first- or last-mile.

6.2.4. The role of *route*

The conditions of the route between home or the workplace and metro station are found to affect transit commuters' decision to use dockless bike-sharing. The bikeway is observed to promote the integration between dockless bike-sharing and metro transit at the evening peak instead of the morning peak. This outcome makes the effects of bikeway to be more specific. Bikeway may make cyclists feel safe, particularly in a dark environment, such as during the evening peak hours. The modeling result also indicates that other types of urban roads, including branch road, main road, and highway, have insignificant effects on the integrated usage. However, the negative effect of the main road on the egress integrated usage in the evening peak is observed. This result is partly in accordance with the work of Zhang et al. (2017) and Lin et al. (2018).

6.2.5. The role of *urban space*

Many land use variables have significant effects on the integrated usage. The mixed land use adjacent to metro stations is positively related to the bike-sharing–metro integrated usage in all the five models. The mixture of either work-related or residence-related sites around metro stations encourages cycling behaviors, possibly due to diverse trip purposes (Zhang et al., 2017).

Commercial land use affects the egress integrated usage in the evening peak when metro commuters often go shopping and conduct entertainment activities after a day of work. However, a high proportion of office land use in metro catchment areas reduces the integrated usage in four out of the five models. A possible reason is that office buildings in Shenzhen are often concentrated in downtown areas, where the metro service is well offered and the metro catchment area is small.

The urban community in metro catchment areas is negatively associated with the integrated usage connecting the workplace (i.e., ME and EA). This phenomenon is probably because a high proportion of urban community land is related to a low proportion of work-related land, thereby inducing fewer demands for integrated usage connecting the workplace.

The urban village is negatively associated with integrated usage in all five models. It is an urban settlement for low-income commuters in Shenzhen, attracting a large number of migrants. For instance, the largest urban village Baishizhou, which accommodates 150,000 people, is located near the high-tech park in Nanshan district (the biggest job center in the downtown). Most residents living in urban villages tend to work nearby or not far away from their homes because of low housing costs. As a result, commuters do not necessarily ride bike-sharing to connect the metro. Moreover, the urban village is often featured with a bad cycling environment, such as narrow and poorly maintained roads, high pedestrian volume, and dense intersections. As a result, metro commuters who live or work in urban villages tend to walk rather than cycle to connect metro stations. On these bases, the urban village variable is negatively correlated with the integrated usage.

7. Conclusions and discussion

7.1. Summary

Dockless bike-sharing is quicker than walking and greener than other motorized modes, and it requires space to park at the origin and destination. Understanding the built environment determinants of the integrated usage is of paramount importance for implementing strategies to improve the integrated usage efficiency. This study first identifies the integrated usage of dockless bike-sharing and the metro in Shenzhen using a big data approach, following Wu et al. (2019) and Guo & He (2020). To better determine its correlates, the *people–metro–bike–route–urban space* framework is proposed to describe the built environment related to the integrated usage. The study then develops a series of multilevel negative binomial regression models to scrutinize the built environment effects on access and egress integrated usage during morning and evening peaks. The findings can be summarized as follows: (1) the access and egress integrated usage have similar trip duration and distance. The majority (approximately 70%) of the integrated usage trips have a time (distance) range of 2.5–10 min (500–2000 m); (2) popular metro stations (with a large ridership) are positively related to access integrated usage, while close proximity to nearby metro stations reduces the integrated usage level (competition or substitution effects); (3) the number of available bikes increases the integrated usage significantly; (4) bikeways in the catchment areas of the metro play a positive role of determining integrated usage in evening scenarios; (5) mixed land use often induces a high demand for the integrated usage; (6) metro catchment areas with a large proportion of urban community areas are related to less integrated usage at the workplace side; and (7) urban village is negatively associated with the integrated usage in all the scenarios.

7.2. Policy insights

Understanding the relationship between the integrated usage and built environment attributes identified in this study has the potential to benefit the encouragement and management of the integrated usage. With a focus on the feeder process (*people–metro–bike–route–urban space*) by bike-sharing, some suggestions are provided herein to operators, urban planners and designers, and the government. As for operators, the identification of hotspot regions and periods for the integrated usage is indispensable to guide the real-time relocation of bike-sharing. Places near home/workplaces and the metro catchment areas with a high land use mix should be a focus, particularly during peak times. Besides, allocating a large number of bikes to regions with abundant populations and job opportunities caters to transit commuters' demand for (to-metro) access trips and (back-home) egress trips. Moreover, the design of bike-rebalance strategies needs to consider the ridership of the metro station. In order to enhance the efficiency and effectiveness of strategies, many bikes should be located around popular metro stations (or those with a large ridership). The disorderly parking problem (Fig. 8) is currently serious in many Chinese cities (Lu et al., 2019; Zhao & Wang, 2019), so placing excessive bikes in station-clustering regions should be avoided. Last but not least, a strategy to improve the possibility of bike-sharing to be chosen as a feeder mode of the metro is to put shared bikes with a priority at two areas: (1) the area immediately adjacent to metro stations (<100 m) (for egress) and (2) the area with a metro station within 800–1500 m (for access).

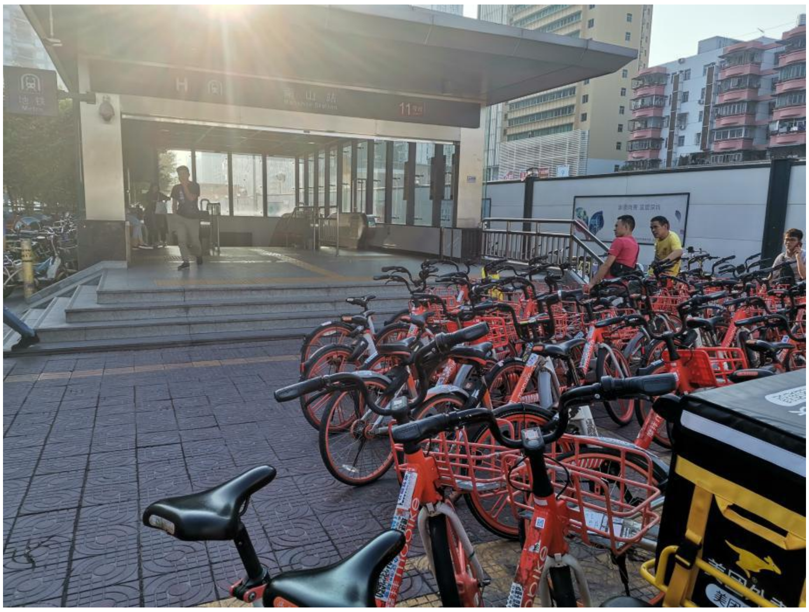

Fig. 8. Disorderly parking in Shenzhen

The role of the government in encouraging the integrated usage is also crucial. In China, since the prosperity of dockless bike-sharing in 2016, several policies and planning, such as *Guidelines on Encouraging and Regulating the Development of Internet Bicycle Rental* enacted by the Ministry of Transport of China and the *Implementation Plan of Improving Bicycle Traffic Development* released by the Shenzhen Transport and Traffic Bureau, have been enacted by the national or local government. In these policies and planning, the function of dockless bike-sharing to be a feeder mode is clarified, and the integration of bike-sharing and transit is explicitly encouraged. For the local government, establishing parking facilities and improving the network of bicycle lanes are paramount. In Shenzhen, enhancing the connection of shared bikeway along the main road may be a more appealing strategy than setting more separated bike lanes along arterial roads (Fig. 9) for Shenzhen because of its relatively limited road space. However, the safety issue on shared pathways/bikeways should be paid enough attention because of the risk of collision with pedestrians during morning and evening peaks (Dong et al., 2020). Additionally, the narrow road, the complex street network, dense population and buildings, and the limited parking space make cycling dangerous in urban villages (Wang et al., 2010). Thus, the cycling environment in or around urban villages needs to be improved. Related practices include adding cycling signs, setting specific parking lots for dockless bike-sharing, and removing road obstacles. Similar interventions for enhancing the cycling environment may be useful to entice more bike-sharing–metro users in office land-dominant areas.

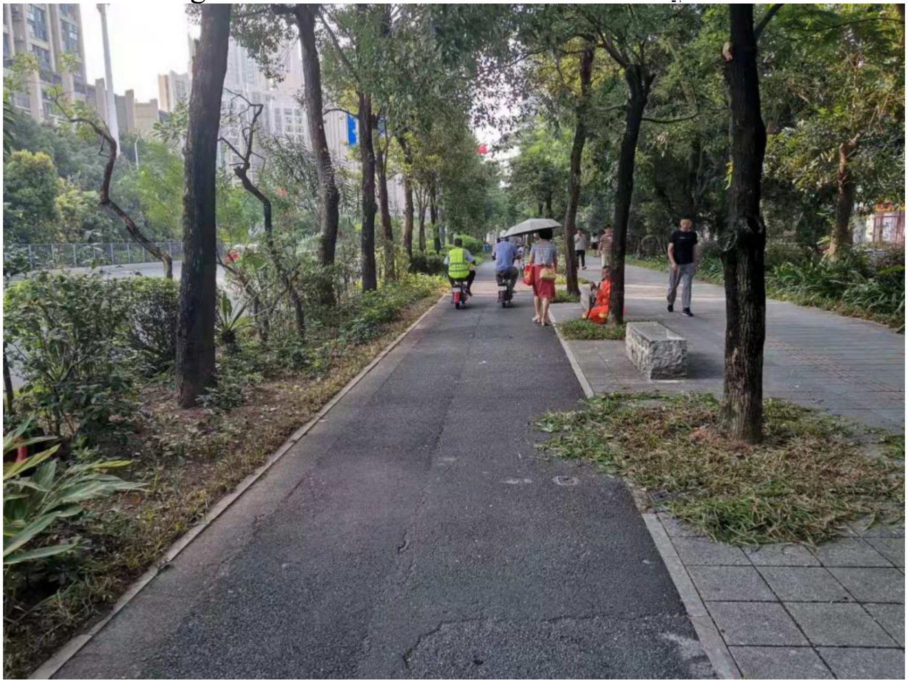

Fig. 9. Shared bicycle lane along the main road in Shenzhen

7.3. Limitations

Though the results in this study are inspiring, several limitations must be noted. First, the empirical analysis was based on the massive data of the bike-sharing location in a Chinese city during three consecutive weekdays, so its representativeness can be challenged and questioned. Researchers can explore the weekly, monthly, seasonal, or even yearly variance of the integrated usage by utilizing our analytical framework with accurate data. Second, applying big data to identify the integrated usage is an approximate estimation from a high possibility of parking behavior within a specific geographical scope (Wu et al., 2019; Guo & He, 2020; Wang et al., 2020). If big data and traditional data (e.g., travel survey, questionnaire survey, and interview) can be combined (Li et al., 2019), the accuracy of the identification can be enhanced. Third, built environment features in the study were objectively measured, but the perceived built environment may also matter in shaping the integrated usage. Field questionnaire surveys are needed for the collection of such data in future research. Last, the heterogeneity of the study area has insufficiently been considered. For example, in this study, the 800-150 m distance for the contextual urban space is applied to both downtown and suburban areas in undifferentiated ways. Indeed, the 800-1500 distance may be a reasonable value for metro stations in the downtown, but it may not be so effective and useful in suburban areas (e.g., low population density, new development zones). Flexibly adjusting the analytical framework is, therefore, indispensable, and more work can be devoted to this issue.

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