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Relationship between eye-level greenness and cycling frequency around metro stations in Shenzhen, China: A big data approach

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ABSTRACT

Better bicycle-transit integration improves the efficiency and sustainability of public transportation systems in urban areas. Urban greenness around metro stations may affect the use of cycling to or from metro stations. However, the evidence for the association between urban greenness and cycling behaviors is inconclusive. In addition, few studies have been conducted in developing countries, such as China, which enjoyed the reputation of cycling nation until the late 1990s and witness a big comeback of cycling in the last several years. This study aimed to explore the relationship between eye-level greenness and cycling behaviors around metro stations in Shenzhen, China, based on free-floating bicycle data and street-view image data. The results indicate that eye-level greenness was positively associated with cycling frequency on weekdays and on weekends within three buffer sizes around metro stations (500-m, 1000-m, and 1500-m). The effect of eye-level greenness on cycling frequency was greater on weekends than on weekdays. Our findings suggest that providing sufficient and visible greenery along streets and cycling lanes around metro stations may promote cycling use and bicycle-transit integration.

1. Introduction

Cycling can benefit both individuals' health (Oja et al., 2011) and the environment (Maibach, Steg, & Anable, 2009). First, cycling can increase moderate to vigorous physical activity, and hence benefits people's physical health byreducing the risk of obesity (Mcpherson, 2014), cardiovascular diseases (Poirier et al., 2006), diabetes and even cancer (Kushi et al., 2010). It can also improve mental wellbeing and reduces stress (Fox, 1999). Second, because cycling consumes little fossil fuels, it is an environmentally friendly transportation mode that reduces air pollution, noise and CO_2 emissions (Cao & Shen, 2019; Fraser & Lock, 2011).

Cycling for transportation purposes can be classified into two types: cycling as the sole transportation mode for the entire trip or in combination with other transportation modes, such as public transit systems (e.g., cycling from home to a metro station and then taking the metro to one's office, which is often denoted *bicycle-transit integration*) (Lin et al., 2018; Zhao & Li, 2017). In recent years, bicycle-transit integration has attracted great attention from both policymakers and researchers because cycling is a sustainable and flexible transport mode that can reduce car use around transit stations (Martens, 2004) and improve people's transfer efficiency (Bachand-Marleau, Larsen, & El-Geneidy, 2011). However, studies have focused mainly on cycling as a sole transportation mode, and evidence for bicycle-transit integration is scarce (Zhao, 2014). Compared with cycling as a sole transportation mode, the combination of cycling with other travel modes usually involves shorter cycling distances and is more influenced by the environment around transit stations (Lin et al., 2018; Zhao & Li, 2017).

Several factors may have led to the general lack of bicycle-transit integration studies, especially in China. First, previous studies mainly used questionnaires about various built environment characteristics within the participants' neighborhood that may be a poor spatial mismatch with the cycling trip legs in bicycle-transit integration (e.g., from the transit station to the office) (Singleton & Clifton, 2014; Wang & Liu,

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2013). Although some recent studies have conducted surveys in transit stations such as metro stations (Zhao & Li, 2017), these can be too costly and labor-intensive and may only comprise a small sample size. Second, with the implementation of Global Positioning System (GPS) devices in free-floating bike-sharing systems, researchers can effectively assess the use of bicycles around transit stations (Caggiani, Camporeale, Ottomanelli, & Szeto, 2018; Pal & Zhang, 2017; Wu, Lu, Lin, & Yang, 2019). However, most studies based on free-floating bike data have focused only on developed countries (Pal, Zhang, & Kwon, 2017; Shen, Zhang, & Zhao, 2018), and only a handful of studies have focused on developing countries, because free-floating bicycles bicycle-sharing systems have just begun to expand in developing countries (Chen, Wang, Sun, Waygood, & Yang, 2018; Du & Cheng, 2018; Wu et al., 2019; Xin, Chen, Wang, & Chen, 2018).

According to socio-ecological models, cycling behaviors are influenced by an array of individual, social and environmental factors (Sallis et al., 2006). Environment characteristics such as light conditions, noise, temperatures and air quality have long been recognized as important factors influencing cycling behavior (Fraser & Lock, 2011). Compared with other environment factors, built environment characteristics have attracted increasing attention because built environment interventions can be implemented by urban planning or redevelopments initiated by policymakers (Eren & Uz, 2019; Leister, Vairo, Sims, & Bopp, 2018; Porter et al., 2019). Among built environment characteristics, urban greenness is arguably one of the most important factors for two reasons. First, greenness can provide shade and pleasant scenery, which may increase the comfort and attractiveness of cycling trips and improve people's willingness to cycle (Lu, An, Hsu, & Zhu, 2019; Lu, Yang, Sun, & Gou, 2019; Porter et al., 2019). Second, improving urban greenness is less costly (Jim & Chen, 2006; Liu, Chen, Feng, Peng, & Kang, 2016; Xiao, Lu, Guo, & Yuan, 2017) and has many other benefits, such as improving residents' health (Helbich et al., 2019; Liu, Wang, Grekousis et al., 2019, 2019b; Wang, Helbich et al., 2019) and reducing noise and air pollution (Pacifico, Harrison, Jones, & Sitch, 2009; Su, Jerrett, de Nazelle, & Wolch, 2011).

The findings from studies that focused on the associations between urban greenness and cycling behaviors are, however, inconsistent. Some studies found a positive association between urban greenness and cycling behaviors (Cole-Hunter et al., 2015; Fraser & Lock, 2011; Kerr et al., 2015; Krenn, Oja, & Titze, 2014; Lu, An et al., 2019; Lu, Yang et al., 2019; Porter et al., 2019; Zhao & Li, 2017). For example, Porter et al. (2019) found that parks and tree canopy coverage had a positive association with cycling frequency in Austin, Texas and Birmingham, Alabama in the United States. Krenn et al. (2014) reported that cyclists are more likely to choose routes with more street greenery. Fraser and Lock (2011) reviewed 21 studies related to the relationship between the built environment and cycling and concluded that green space has a weak or moderate association with cycling. Yet, some studies found no association between urban greenness and cycling (Christiansen et al., 2016; Sun, Du, Wang, & Zhuang, 2017). For instance, Christiansen et al. (2016) compared cycling behaviors from 14 cities in 10 countries and found no significant association between urban greenness and cycling behavior. Sun et al. (2017) also reported no association between one's proximity to greenspace and cycling behavior. In contrast, some studies reported negative associations between urban greenness and cycling (Mertens et al., 2016, 2017). For example, the presence of trees showed a negative association with cycling time in five large European cities (Mertens et al., 2017).

In recent years, researchers began to realize that assessing methods of urban greenness may at least partially explain the inconsistent findings for greenness-cycling associations. For example, Lu, An et al. (2019); Lu, Yang et al. (2019) found positive associations between cycling behaviors and eye-level greenness assessed by street-view images, but not with overhead view greenspace assessed by normalized difference vegetation index (NDVI) extracted from satellite images. Studies of built environments and cycling mainly assess greenness via GIS-based methods (e.g., park area or NDVI) that capture greenspace exposure from an overhead perspective (Lu, An et al., 2019; Lu, Yang et al., 2019; Porter et al., 2019). However, some researchers have argued that eye-level greenness measures may better represent cyclists' perceived greenness than overhead measures (Helbich et al., 2019; Lu, An et al., 2019; Lu, Yang et al., 2019; Van Renterghem & Botteldooren, 2016; Wang, Helbich et al., 2019), although less evidence is available to support this claim, mainly due to methodological limitations (Lu, An et al., 2019; Lu, Yang et al., 2019).

Traditional methods for assessing eye-level greenness include questionnaires (Takano, Nakamura, & Watanabe, 2002) and field-audit methods (de Vries, Van Dillen, Groenewegen, & Spreeuwenberg, 2013), but they are expensive and time-consuming (Helbich et al., 2019; Lu, An et al., 2019; Lu, Yang et al., 2019; Wang, Helbich et al., 2019). Recent development of machine learning and street-view image services (e.g., Google Street Image) allow the rapid extraction of eye-level greenness data from street-view images on a large geographic scale (Helbich et al., 2019; Lu, An et al., 2019; Lu, Yang et al., 2019; Wang, Helbich et al., 2019). This novel method has proven useful in assessing eye-level greenness exposure and has recently been used in epidemiological studies (Helbich et al., 2019).

In sum, several gaps must be addressed in studies of the association between the built environment and cycling. First, studies have focused mainly on cycling behaviors in residential neighborhoods, but less attention has been paid to cycling behavior as a transfer mode in bicycle-transit integration (i.e., cycling to or from transit stations). Second, although bicycle-transit integration has attracted some research attention in developed countries, evidence from developing countries remains scarce. Third, most cycling trips occur on streets or designated cycling lanes along streets, so greenness extracted from eye-level street-view images are more likely to reflect cyclists' daily greenness exposure (Lu, 2019). However, previous studies mainly used overhead-view greenspace indicators such as park area or NDVI to assess greenspace exposure, thus leading to inconsistent findings.

This study aimed to use free-floating bicycle data to explore the relationship between eye-level greenness and cycle use around metro station areas in Shenzhen, China, by focusing on the effect of eye-level greenness on the frequency of shared bicycle trips to or from metro stations. We further explored whether there was any temporal variation in the greenspace-cycling associations, by comparing the associations on weekdays and thoese on weekends. This study extended previous research in several respects. First, it enhanced our knowledge of the built environment–cycling association by focusing on bicycle-transit integration around metro stations. Second, it used free-floating bike big data to assess cycling use in China, which enriched our understanding of cycling behaviors in developing countries. Third, this study focused on eye-level greenness exposure based on street-view image data and further enhanced our knowledge of the effects of urban greenspace on cycling behavior.

2. Methods

2.1. Variables

2.1.1. Outcome: cycling frequency

In this study, the cycling data was obtained from a large bike-sharing company, Mobike, with a major market share in Shenzhen, China. Mobike was the first free-floating bicycle-sharing system which entered in Shenzhen from October 2016. Mobike had a fleet of 900,000 bicycles in Shenzhen as of December 2017 (Wu et al., 2019). Shenzhen municipality provide designated bike parking areas near metro stations for public-sharing bicycles only, but not for personal-owned bicycles. Hence, many people using Mobike bicycles around metro stations. The data consisted of approximately 20 million cycling trips in Shenzhen over a 14-day period from 1 to 14 December 2017. The weather during this period was sunny, and the temperature ranged from 16 °C to 25 °C, which was suitable for cycling. The location (latitude, longitude) and the time-stamps for the origin and destination were recorded in the original data for each trip.

We focused on cycling trips around metro stations and trips that began or ended within three buffer zones (with a radius of 500-m, 1000-m, and 1500-m) were counted from the original data. The dependent variable was the frequency of bike trips per day around metro stations for each station. The cycling frequency data were further separated into workdays and weekends to identify any potential temporal differences.

The data processing consisted of three steps: data cleaning, establishing buffer zones around each metro station, and assigning cycling trips to each metro station. First, we excluded cycling trips with an abnormal duration (< 1 min or > 30 min) or speed (> 3 m/s). The cycling speed was calculated as the ratio of straight-line trip distance (based on start and end points of a trip) and duration, as shown in Equation (1). The actual trip distance is longer than straight-line distance, however we cannot identify the actual trip distance due to the lack of trip route data.

$$\mathrm{Speed}_n = \frac{\sqrt{(X_a - X_b)^2 + (Y_a - Y_b)^2}}{\mathrm{Duration}_n} \tag{1}$$

where a and b represent the start and end points, and X and Y represent the latitude and longitude, respectively.

Second, to examine the effects of urban greenspace on cycling behavior on various spatial scales, we chose three buffer-zone radii from a metro station (500, 1000, and 1500 m) (Fig. 2). To avoid any potential overlapping between buffer zones (Fig. 1a), the Thiessen polygon method was used to create non-overlapping buffer-zones (Fig. 1b) (Alani, Jones, & Tudhope, 2001; Lu, An et al., 2019; Lu, Yang et al., 2019; Pardo-Igúzquiza, 1998; Rhynsburger, 1973). In this way, each cycling trip could be assigned to a sole metro station. The Thiessen polygons were created by taking metro stations as discrete points in ArcGIS 10 (Esri Inc., Redlands, CA). Finally, the number of cycling trips on both weekdays and weekends were calculated for each metro station.

2.1.2. Eye-level greenness exposure

We collected street-view images from Tencent Online Map (https://map.qq.com), the most comprehensive online street-view image database in China, as previously described (Helbich et al., 2019; Wang, Helbich et al., 2019, 2019b; Wang, Liu et al., 2019). Street-view sampling points were created with 100-m spacing along the street network in Shenzhen. The street-network data in 2016 were obtained from OpenStreetMap (Haklay & Weber, 2008). For each sampling point, we collected street-view images with four headings of 0°, 90°, 180°, and 270° (Helbich et al., 2019; Wang, Helbich et al., 2019, 2019b, 2019c). We collected 262,140 street-view images from 65,535 sampling points in this study.

Following previous studies (Helbich et al., 2019; Wang, Helbich et al., 2019, 2019b; Wang, Liu et al., 2019), a fully convolutional neural network of semantic image segmentation (FCN-8 s) was used to assess eye-level greenness exposure based on the ADE20 K dataset of annotated images for training purposes (Zhou et al., 2019). This method can segment images into different ground objects with artificial intelligence. It can outperform color-based segmentation method, for example, green cars in this study would be identified as car instead of vegetation. After image segmentation, the proportion of all vegetation (e.g. grasses, trees and shrubs) in each images was calculated as street-view greenness (SVG). The accuracy of the FCN-8 s was with 0.814 for the training data and 0.811 for the test data. The SVG for a sampling point was determined as the average SVG of four images with four headings for that point. We calculated the SVG for each metro station by averaging the SVG values for all sampling points within the 500-m, 1000-m, and 1500-m circular buffers around the centroid of each metro station.

2.1.3. Covariates

Following previous studies (Lu, An et al., 2019; Lu, Yang et al., 2019; Porter et al., 2019; Zhao & Li, 2017). We calculated the built environment factors that may influence cycling within the buffer-zones around each metro station. These factors were population density, street intersection density, land-use mix, the number of bus stops and retail stores, and the terrain slope. The population density was defined as the residential population per unit of land area. The street intersection density was defined as the number of intersections per unit of land area. The land-use mix (entropy score) was calculated by the number of land-use types (residential, working, commercial, and leisure) based on points of interest (POIs) obtained from Gaode POI data using an API interface (https://www.amap.com/). The data consisted of various categories of facilities such as residential communities, commercial and business areas, tourist attractions, food and shopping precincts, educational facilities, government and public service buildings, financial services zones, and public facilities. We also calculated the number of bus stops and retail shops with POI data. The average degree of slope within the buffer zones was calculated based on the 30-m slope raster file, which was obtained from the geospatial data cloud (GDC) in China (https://www.gscloud.cn/).

2.2. Data analysis

Since the dependent variable was a count variable, we used a multivariate Poisson regression model to examine the association between SVG and the cycling frequency around metro stations. The full model was specified as follows (Equation (2)):

(a)the overlapping buffers with the same radius

(b) the Thiessen-Polygon buffers

Fig. 1. Buffer areas around metro stations.

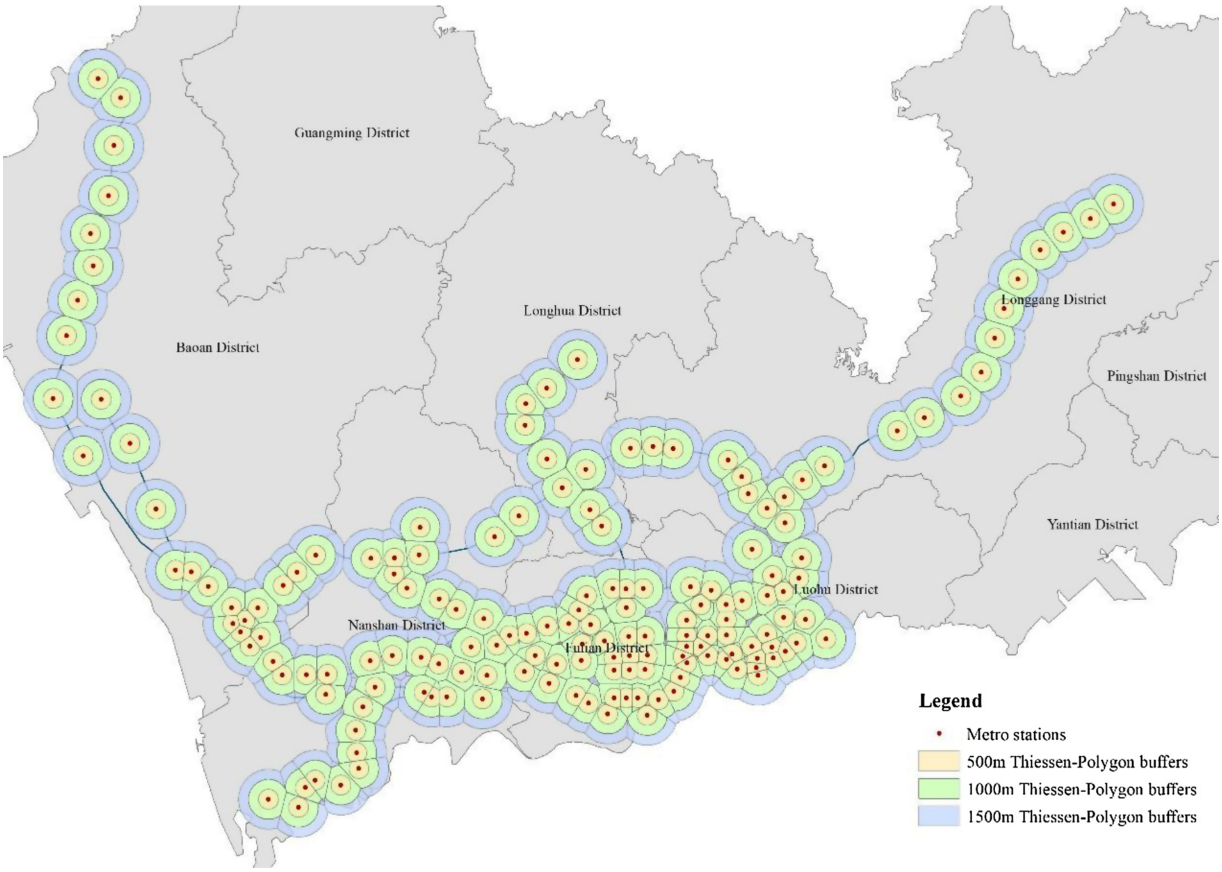

Fig. 2. 500-m,1000-m,1500-m Thiessen-Polygon buffers.

$$P(Y = y_i \mid \lambda) = \frac{\lambda^{\beta_0+\beta_1 \cdot SVG_i+\beta_2 Covariates_i+\varepsilon_i} \bullet e^{-\lambda}}{(\beta_0 + \beta_1 \cdot SVG_i + \beta_2 Covariates_i + \varepsilon_i)!} \quad (2)$$

where y_i represents the use of shared bikes around a metro station, SVG_i represents a vector of variables of SVG, $Covariates_i$ represents a vector of covariates, λ represents the Poisson event rate, and ε_i represents random errors.

The cycling frequencies on weekdays and weekends were examined separately in two regression models, because previous studies indicated that people's cycling behaviors may vary between weekdays and weekends (Ho & Mulley, 2013). Furthermore, we used three buffer-zone sizes around metro stations to explore whether the association between cycling frequency and SVG varied across spatial scales (Wu et al., 2019).

3. Results

3.1. Descriptive statistics

Table 1 summarizes the characteristics of the variables. The average cycling frequency increased with the buffer-zone size and was higher on weekdays than on weekends. The average cycling frequencies on weekdays were 2566.383 (500-m buffer zone), 4664.826 (1000-m buffer zone), and 5686.946 (1500-m buffer zone), whereas the average cycling frequencies on weekends were 2319.479 (500-m buffer zone), 4293.761 (1000-m buffer zone), and 5257.203 (1500-m buffer zone). The average SVG values around metro stations (0.280 in the 500-m buffer zone, 0.267 in the 1000-m buffer zone, and 0.241 in the 1500-m buffer zone) decreased with the buffer-zone size.

The average population densities were 76542.487 (500-m buffer zone), 67311.535 (1000-m buffer zone), and 55590.381 (1500-m buffer zone), whereas the average street intersection densities were 48.903 (500-m buffer zone), 45.080 (1000-m buffer zone), and 42.484 (1500-m buffer zone). Thus, both variables decreased with the buffer-zone size.

In addition, the average numbers of retail shops were 49.851 (500-m buffer zone), 99.299 (1000-m buffer zone), and 159.880 (1500-m buffer zone), whereas the average numbers of bus stops were 47.072 (500-m buffer zone), 77.479 (1000-m buffer zone), and 42.484 (1500-m buffer zone). Thus, both variables increased with the buffer-zone size.

The average land-use mix values were 0.802 (500-m buffer zone), 0.792 (1000-m buffer zone), and 0.803 (1500-m buffer zone), whereas the average terrain slopes were 5.904° (500-m buffer zone), 5.734° (1000-m buffer zone), and 6.062° (1500-m buffer zone).

3.2. Associations between SVG and cycling frequency around metro stations

Table 2 presents the associations between SVG, the built environment characteristics, and cycling frequency around metro stations on weekdays in the three buffer zones. SVG showed a positive association with cycling frequency in all three buffer zones.

With respect to the covariates, the population density, street intersection density, land-use mix score showed positive associations with cycling frequency. However, the number of retail shops showed a negative association with cycling frequency in the 1000-m and 1500-m buffer zones. The terrain slope showed a negative association with cycling frequency. The number of bus stops did not show a significant association with cycling frequency in any buffer zone.

Table 3 presents the associations between the SVG, the built environment characteristics, and cycling frequency around metro stations on weekends. SVG again showed a positive association with cycling frequency in all three buffer zones.

For covariates, the population density, street intersection density,

Table 1
Summary statistics for all variables.

	500-m buffer	1000-m buffer	1500-m buffer
Variables	Mean (SD)	Mean (SD)	Mean (SD)
Dependent variable			
Cycling frequency on weekdays (number of rides/day)	2566.383(1557.723)	4664.826(3074.209)	5686.946(4518.491)
Cycling frequency on weekends (number of rides/day)	2319.479(1372.563)	4293.761(2899.526)	5257.203(4236.457)
Urban greenspace			
Street View Greenspace (SVG)	0.280(0.093)	0.267(0.078)	0.241(0.061)
Covariates			
Population density (person/km2)	76542.487(40535.064)	67311.535(43720.074)	55590.381(25796.596)
Street intersection density (number/km2)	48.903(26.588)	45.080(23.240)	42.484(21.453)
Land-use mix (entropy score)	0.802(0.047)	0.792(0.056)	0.803(0.040)
Number of retail shops	49.851(46.171)	99.299(82.332)	159.880(118.193)
Number of bus stops	23.168(10.761)	47.072(19.805)	77.479(30.339)
Terrain slope (degree)	5.904(2.302)	5.734(2.357)	6.062(2.369)

SD = standard deviation

land-use mix score showed positive associations with cycling frequency. The number of retail shops showed a negative association with cycling frequency in the 1000-m and 1500-m buffer zones. Finally, the terrain slope showed a negative association with cycling frequency. The the number of bus stops showed no significant association with cycling frequency in any buffer zone.

4. Discussion

4.1. Eye-level greenness and cycling frequency around metro stations

Our results suggest that eye-level greenness exposure was positively associated with cycling frequency on both weekends and weekdays in all three buffer zones. Previous studies also found that greenspace exposure assessed in terms of the size of urban parks showed a positive relationship to cycling use in metro station areas (Zhao & Li, 2017). However, Wu et al. (2019) reported that greenspace exposure assessed via NDVI had no association with cycling use in metro station areas. In a comparison study, Lu, An et al. (2019), Lu, Yang et al. (2019) indicated that the odds of cycling showed a positive association with eye-level greenness extracted from street-view images, but not with overhead-view greenness via NDVI, possibly because eye-level greenness extracted from street-view images can more accurately measure people's exposure to small-scale vegetation such as street trees and pocket gardens (Helbich et al., 2019; Wang, Helbich et al., 2019).

Environmental psychological theories such as stress reduction theory (SRT) and attention restoration theory (ART) have highlighted the role of perceived greenness for attention restoration and psychological stress-reduction (Kaplan, 1995; Ulrich, 1981). SRT indicates that humans likely obtained protection and food from vegetation in the process of evolution, and exposure to vegetation can also evoke positive emotions and reduce stress in modern humans (Ulrich, 1981). ART suggests vegetation has four types of restorative features: being away, extension, compatibility and fascination, which combine to help reduce people's psychological fatigue (Kaplan, 1995). Hence, the availability of greenery can improve the perceived preference of the surrounding environment, which is also important for cycling behaviors (Lu, An et al., 2019; Lu, Yang et al., 2019; Porter et al., 2019). For example, street trees have the function of providing shade (Li, Ratti, & Seiferling, 2018), and their shade may also cool cyclists during hot weather, especially for trips over long distances. Hence, urban greenery, especially along streets, provides cyclists with a comfortable and attractive experience, which thereby encourages cycling use.

In contrast, NDVI measures large greenspace infrastructure such as urban parks or preserved natural areas (Ye et al., 2018). Cycling behaviors mainly occur on streets, so cyclists may not traverse through or even perceive large greenspaces unless cycling lanes are present within these areas (Lu, An et al., 2019; Lu, Yang et al., 2019). Hence, due to the low visibility to cyclists of large greenspaces assessed through the GIS-method (e.g., NDVI), large greenspace infrastructure may have weaker influence on people's psychological feelings, an important component of the cycling experience (Helbich et al., 2019; Wang, Helbich et al., 2019). For example, Helbich et al. (2019) found that eye-level greenness based on street-view data showed a positive association with psychological wellbeing, but this association was not found for overhead greenspace based on NDVI or land-use data. Thus, the difference ways of measuring greenspace (overhead view vs. eye-level) may partially explain the inconsistent findings from previous studies that examined greenspace-cycling use in metro station areas.

Our results further indicate that the effect size of eye-level greenness on cycling frequency was higher on weekend than on weekdays, as demonstrated by larger coefficients for cycling frequency on weekends than on weekdays. The different effect size may be explained by the different cycling purposes on weekdays and weekends. People are more likely to cycle for recreational purposes on weekends than on weekdays (Ho & Mulley, 2013; Liu, Zhang, Jin, & Liu, 2020), so they may pay

Table 2
The associations of urban greenspace, built environment characteristics and cycling frequency around MTR stations on weekdays (Shenzhen, China, N = 167).

Model predictor	Model 1 (500-m buffer)	Model 2 (1000-m buffer)	Model 3(1500-m buffer)
	Coef.(SE)	Coef.(SE)	Coef.(SE)
Greenness			
SVG	1.983***(0.026)	2.095***(0.023)	2.551***(0.028)
Built environment			
Population density (in log)	0.040***(0.001)	0.177***(0.002)	0.315***(0.002)
Street int. density (in log)	0.204***(0.003)	0.211***(0.003)	0.298***(0.003)
Land-use mix	0.135***(0.035)	1.129***(0.035)	2.032***(0.045)
Number of retail shops	0.001(0.001)	−0.001***(0.000)	−0.001***(0.000)
Number of bus stops	0.011(0.010)	0.003(0.002)	−0.004(0.006)
Terrain slope	−1.363***(0.046)	−0.231***(0.031)	−0.019***(0.000)

Coef. = coefficient; SE = standard error; *p < 0.1. **p < 0.05. ***p < 0.01.

Table 3
The associations of urban greenspace, built environment characteristics and cycling frequency around metro stations on weekends (Shenzhen, China, N = 167).

Model predictor	Model 4 (500-m buffer)	Model 5 (1000-m buffer)	Model 6 (1500-m buffer)
	Coef.(SE)	Coef.(SE)	Coef.(SE)
Greenness			
SVG	2.520***(0.027)	2.728***(0.024)	3.807***(0.029)
Built environment			
Population density (in log)	0.048***(0.001)	0.225***(0.002)	0.372***(0.003)
Street int. density (in log)	0.168***(0.003)	0.153***(0.003)	0.227***(0.003)
Land-use mix	1.007***(0.037)	0.156***(0.037)	0.159***(0.047)
Number of retail shops	−0.000(0.000)	−0.002***(0.000)	−0.002***(0.000)
Number of bus stops	0.011(0.010)	0.001(0.001)	−0.003(0.006)
Terrain slope	−1.481***(0.048)	−0.281***(0.033)	−0.019***(0.001)

Coef. = coefficient; SE = standard error; *p < 0.1. **p < 0.05. ***p < 0.01.

more attention to the cycling experience and hence the surrounding greenness. However, people are more likely to cycle for transportation purposes on weekdays (Ho & Mulley, 2013), so they may pay more attention to the efficiency of cycling trips instead of the surrounding environment.

The sensitivity analysis shows that the associations between eye-level greenness and cycling use in metro station areas were significant in all three buffer zones, ensuring the robustness of our results. Although previous studies indicated that the frequency of cycling with shared bikes may decrease with distance (Chen et al., 2018; Du & Cheng, 2018; Shen et al., 2018; Wu et al., 2019), our results suggest that greenspace-cycling associations remain significant across all three buffer zones. Hence, the effect of street environments such as greenspace on cycling behavior may be relatively stable within 1500-m buffer.

4.2. Other built environment factors

Our results suggest that population density, street intersection density and land-use mix score had positive associations with cycling use, while number of retail shops and terrain slope had negative associations with cycling use around metro stations, and this finding was consistent with those of previous studies (Lin et al., 2018; Zhao & Li, 2017; Zhao, 2014). The demand for cycling is larger in metro station areas due to their high metro passenger volumes (Xue & Sun, 2020). Street intersection density is associated with street connectivity which can increase people's odds of taking active transportation mode such as cycling (Berrigan, Pickle, & Dill, 2010). The reason may be that connectivity could lead to the ease of cycling by creating more and shorter routes from place to place (Berrigan et al., 2010). Also, higher land-use mix score indicates diverse land uses which may provide more non-residential destinations (Fraser & Lock, 2011). In addition, population density, street intersection density and land-use mix are potential indicators of urbanization (Zhang & Shun, 2003), and more urbanized areas are more likely to have a better cycling infrastructure, which may further encourage cycling behaviors (Wang, 2010).

The number of retail shops showed a negative association with cycling use around metro stations, which is consistent with previous studies in Beijing (Lin et al., 2018; Zhao & Li, 2017). This negative association might be explained in part by the competition in such areas between walking and cycling (Wu et al., 2019). That is, retail shops provide more convenience for pedestrians than for cyclists, so people in metro station areas with more retail shops may choose walking over cycling. Also, steeper terrain slope is associated with more exhausting cycling experience and decrease people's enthusiasm for cycling (Lu, An et al., 2019; Lu, Yang et al., 2019).

4.3. Implications for urban design and planning

We can draw some important urban planning implications from our findings. First, eye-level greenness exposure showed a positive association with cycling frequency around metro stations. Thus, to improve bicycle-transit integration, more attention should be paid to green infrastructure around metro stations, especially those visible from streets or cycling lanes. Compared with large green infrastructure such as parks, small-scale street vegetation including trees or pocket gardens are more relevant to what cyclists perceive. Also, street vegetation can be more easily improved than large green infrastructure because of the lower cost and smaller areas required, so urban planners should pay more attention to the former around transit stations. Second, population density was positively related to cycling frequency, which indicates that metro stations with more nearby residents also have a higher demand for shared bikes. Therefore, population density should also be taken into account in cycling-transit integration system.

4.4. Strengths and limitations

This study has several strengths. First, it used free-floating shared bike data to investigate bicycle-transit integration, thus addressing many limitations of previous studies. For example, previous studies mainly used survey methods, covering limited study areas with a small sample size. In this study, we covered all 167 metro stations in Shenzhen with a sample size of 12 million cycling trips (all trips in 1500 m buffer). The large sample size ensured the generalizability of our findings. Second, we used street-view images to assess eye-level greenness exposure. Eye-level greenness based on questionnaires and field audit is either subjective or labor-intensive, whereas our method enabled efficient, objective, and accurate assessment of cyclists' daily exposure to urban greenness over a large research area. Third, we compared the associations of eye-level greenness and cycling use in metro station areas on both weekdays and weekends. The free-floating bike data included the date and time of each cycling use, so we could distinguish the cycling trips on weekdays and on weekends. Finally, three buffer-zone sizes were used for sensitivity analysis, imparting robustness to our study.

The following limitations of this study should also be noted. First, our research was based on the analysis of cross-sectional data, and we could not infer any causation between eye-level greenness and cycling behaviors. Second, neighborhood-level demographic and socio-economic variables such as income, age and gender distribution, and education level were not included in this study due to data unavailability. Future studies may need to consider these variables. Third, some environment factors such as light condition (Fotios, Uttley, & Fox, 2019) and noise exposure (Aletta, Van Renterghem, & Botteldooren, 2018) were not included in this study which may be important for cycling behaviors. Some other limitations stem from the nature of big cycling data. For example, the lack of cyclists' individual and socio-economic information, as well as cycling purposes (e.g. for recreational or transportation purposes) in our dataset prevented us from controlling for such covariates. Furthermore, some cyclists used their personal bicycles, and their cycling trips were not available in our dataset. Further studies may include cyclists with personal bicycles.

5. Conclusions

This study is the first to systematically explore the association between eye-level greenness and cycling behaviors in metro station areas in China based on free-floating bike data and street-view data. The results indicate that eye-level greenness showed a positive association with cycling frequency both on weekdays and on weekends. Also, the population density and numbers of bus stops showed a positive association with cycling frequency both on weekdays and on weekends. In contrast, the numbers of retail shops showed a negative association with cycling frequency in the 1000-m and 1500-m buffer zones.

Hence, to promote cycling-transit integration, policymakers and planners are advised to pay close attention to the location and visibility of street vegetation around metro stations.

Declaration of Competing Interest

None.

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