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# Green space exposure at subway stations, transportation mode choice and travel satisfaction

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ABSTRACT

Access to subway stations is important for daily commuting, but scant attention has been given to green space exposure at subway station areas in people's residential neighbourhoods and workplace areas. This paper focuses on the association between street-level green space exposure around subway stations at residential and work locations and people's choice of subway as their primary commuting mode and travel satisfaction, using street view data and survey data in Beijing, China. Street view data and a machine learning approach were used to measure both street view green space quantity (SVG-quantity) and street view green space quality (SVG-quality). The results suggested that SVG-quantity and SVG-quality generate differential effects on subway use and travel satisfaction under residential and workplace contexts. Findings of this study highlight the complementary effects of green space and travel infrastructure provision in shaping travel behaviour and wellbeing in residential neighbourhood and workplace contexts.

## 1. Introduction

Sustainable Development Goals have highlighted the importance of sustainable transport development (Ki-Moon, 2016; Wang, Zheng, Wu, & Wang, 2022). Improving the usage of public transportation is associated with reducing car dependency and energy consumption (Ibraeva, de Almeida Correia, Silva, & Antunes, 2020), facilitating regional economic, environmental and amenity development (Bartholomew & Ewing, 2011), and improving public health (Appleyard, Frost, & Allen, 2019). Amongst the various forms of public transportation within the city, the subway is the most efficient mode for transporting large numbers of travellers, since it can transport as nine times as a private car for a single ride (Jenelius, 2019). Therefore, policy makers worldwide have paid great attention to the question of how to encourage people to use subways (Cheng et al., 2022, 2023; Wu et al., 2023; Zhang et al., 2014). Also, since people have to share limited space within public transportation, it is important to understand how to improve their travel satisfaction to ensure continued use (Abenoza, Cats, & Susilo, 2017). Travel satisfaction directly reflects passengers' mood and feelings about their travel experiences and can further have an impact on their quality of life (Wang et al., 2022a; Wu et al., 2022b).

Determinants of transportation mode choice and travel satisfaction vary across both individual-level and environment-level characteristics (Ye & Titheridge, 2017). Individual-level characteristics such as income, gender and age are significant correlated

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with transportation mode choice (Bantis & Haworth, 2017) and travel satisfaction (Susilo & Cats, 2014). As regards the built environment, previous studies have mainly focused on residential neighbourhood environments, and have indicated that people living in neighbourhoods with higher density, more diverse land use types, greater public transportation accessibility and better walking environments may have less private car dependency (Frank et al., 2006). In recent years, the effect of green space has begun to attract more attention, since improving green space within the neighbourhood not only decreases car usage (Kruize et al., 2019) and increases travel satisfaction (Ta, Li, Chai, & Wu, 2021), but also brings numerous co-benefits (Wu, Chen, Yun, & Wang, 2022; Wang, Feng, Pearce, Liu, & Dong, 2021). Although there is a lack of empirical evidence regarding whether and how green space may directly influence people's use of public transportation, it has been found that green space around transit stations can also provide travellers with better experiences (Wang, Lu, Wu, Liu, & Yao, 2020), so it is reasonable to hypothesize that green space around transit stations matters for people's use of public transportation and travel satisfaction.

There are several research gaps to be noted. First, previous literature mainly investigated the built environments around participants' home addresses, while few studies have shed light on the effects of the environment around major transportation infrastructures (e.g., subway stations) on transportation-related behaviours (e.g., commuting by subway). Second, the majority of studies have only focused on the residential context and have ignored the fact that the work context also matters for people's transportation-related behaviours. Although existing literature has documented the effect of general green space exposure on transportation-related behaviours, scant attention has been paid to street-level visible green space, especially from the quality perspective. The aim of the present study was to: 1) propose a novel method to assess street-level visible green space around subway stations; 2) identify the differences in the effect of street-level green space exposure around subway stations on transportation mode choice and travel satisfaction between residential and work contexts. To the best of our knowledge, it was also among the few studies to investigate the effect of street-level green space exposure around subway stations on transportation mode choice/travel satisfaction in the Chinese context using street view data and machine learning techniques. Fig. 1 presents the conceptual framework for this study.

## 2. Literature review

Existing literature has found that green space has an influence on people's choice of transportation mode (He, Lu, Xie, & Helbich, 2021; Hogendorf, Groeniger, Noordzij, Beenackers, & Van Lenthe, 2020; Lu, Yang, Sun, & Gou, 2019; Ta et al., 2021; Wang, Lu, Wu, Liu & Yao, 2020; Yang et al., 2022; Yang et al., 2020; Yang et al., 2019) and travel satisfaction (Ta et al., 2021). First, green space, as an important natural element, can provide people with a restorative effect, which helps to reduce stress and restore energy (Ulrich et al., 1991). Therefore, people are more likely to walk or cycle in neighbourhoods with more green space (Lu et al., 2018; Lu et al., 2019). For example, Hogendorf et al. (2020) found that the distance from residential location to the nearest green space was positively associated with people's walking for active commutes. Wang et al. (2020) indicated that green space around subway stations was positively related to cycling frequency. Also, daily commuting often takes a long time and can make people feel stressed, while green space can offer them diverse and relaxing scenery, which increases their travel satisfaction (Ta et al., 2021). For instance, Ta et al.

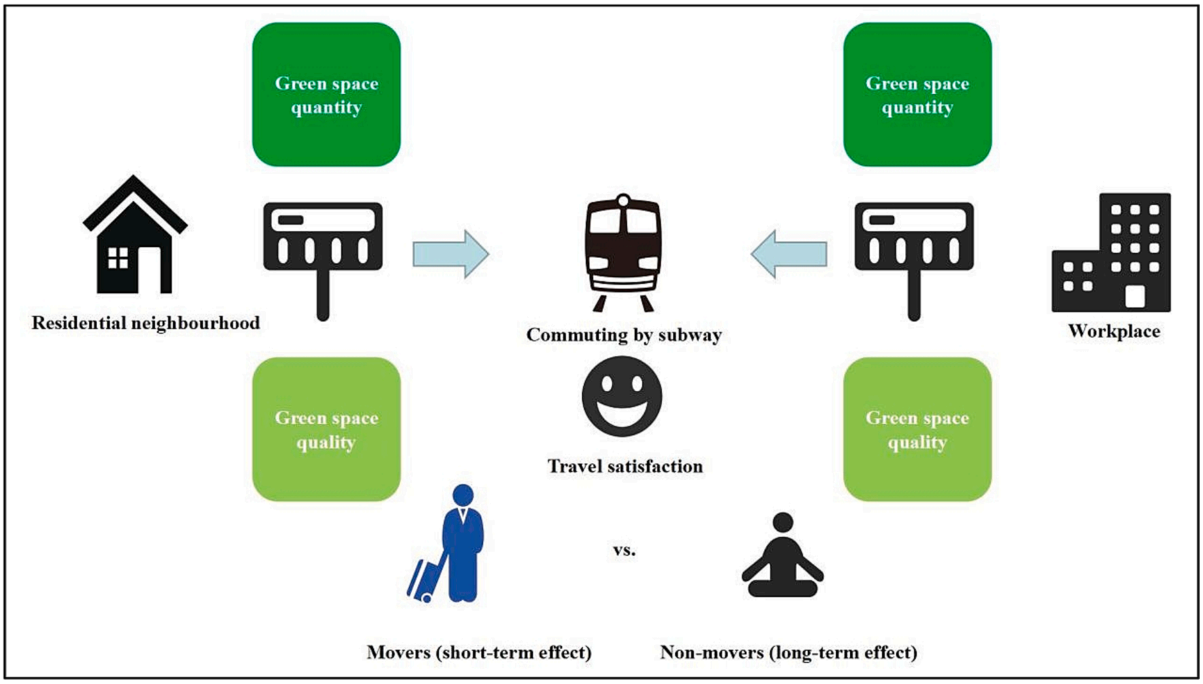


**Fig. 1.** The conceptual framework.

(2021) suggested that green space exposure is positively associated with people's satisfaction with active travel. Second, green space such as street trees can offer pedestrians shade, improving their travelling experience (Lanza & Durand, 2021; Larsen, Gilliland, & Hess, 2012; Lin & Chang, 2010). Shade provided by green space can mitigate heat caused by exposure to direct sunlight and improve travellers' satisfaction (Lanza & Durand, 2021; Larsen et al., 2012; Lin & Chang, 2010). For example, Lanza et al. (2021) indicated that tree canopies weaken the negative effect of heat waves on ridership. Larsen et al. (2012) found that the presence of street trees was positively related to children's active travel to school, since the shade provided by trees can make travel more comfortable. Last, green space has been proven to be able to prevent the negative impact of traffic noise and air pollution (Pathak, Tripathi, & Mishra, 2011), which may provide pedestrians with a more pleasant environment (Franěk, Režný, Šefara, & Cabal, 2018). Green space such as street trees may remove or filter air pollutants and thus reduce air pollution (Grote et al., 2016). Also, urban trees can block sound waves directly (Jang, Lee, Jeon, & Kang, 2015) and exert a buffering effect between noise and psychological stress (Nang Li, Kwan Chau, Sze Tse, & Tang, 2012).

Most prior studies have mainly focused on the effect of green space in residential neighbourhoods, while scant attention has been paid to other geographical contexts (e.g., the workplace) (Ta et al., 2021; H. Wang et al., 2022b; Yang et al., 2022). This is because previous studies have assumed that most travel tends to occur within the residential context (Adams, Bull, & Foster, 2016). However, this assumption may ignore people's daily mobility (Wang, Feng, Pearce, Zhou, et al., 2021), and existing evidence suggests that during weekdays, employees may spend half of their time in the workplace (Hipp et al., 2017). Hence, the issue of uncertain geographic context highlights that associations between the built environment and human behaviour vary across different contexts (Kwan, 2012). Therefore, it is important to acknowledge the effect of the built environment on people's transportation mode choice and travel satisfaction both in the residential neighbourhood and at the workplace (Ding, Cao, & Wang, 2018; Ding, Lin, & Liu, 2014; Forsyth & Oakes, 2014; Gehrke & Welch, 2017; Wang, Shao, Yin, & Guan, 2022; Yang et al., 2022). The association between the built environment and human behaviour may be different between residential neighbourhoods and the workplace for several reasons. First, the first destination after leaving the residential neighbourhood and the workplace may be different, which has an influence on people's choice of transportation mode (Yang et al., 2022). Second, people's mood and mental status is different before and after work, so their attention to the surrounding environment in the residential neighbourhood and the workplace will also vary (Adams et al., 2016). Last, the time when people start work in the morning is more consistent, while the time when they finish work may be more variable, which may influence their transportation mode choice due to the consideration of crowdedness (X. Wang et al., 2022). For example, Yang et al. (2022) found that green space around the workplace contributes to commuting walking behaviour in Shanghai, China. Wang et al. (2022c) suggested that interaction density is associated with the use of public transit in residential neighbourhoods but not the workplace.

In recent years, increasing numbers of scholars have begun to realize that the measurement of green space may have an influence on the association between green space and transportation-related behaviour (Bai, Cao, Wang, Liu, & Wang, 2022; Lu et al., 2018; Lu et al., 2019). Previous studies on the association between green space and transportation-related behaviour mainly focused on green space exposure from an overhead view (Lu et al., 2018; Lu et al., 2019). This method usually uses remote sensing (e.g., normalized difference vegetation index) or land use data (e.g., parks) to measure green space exposure, which may be able to reflect street-level green space exposure (Nordbø, Nordh, Raanaas, & Aamodt, 2018). Most active transportation occurs on the streets, and most transit stations are also located alongside these streets, so street-level green space exposure may be more important in influencing transportation-related behaviour than an overhead-view perspective of green space (Bai et al., 2022; Lu et al., 2018; Lu et al., 2019). For example, Lu et al. (2018) found that street-level green space exposure but not number of parks was associated with more walking time. Lu et al. (2019) pointed out that street-level green space exposure was positively linked to the odds of cycling, but such association was not found for normalized difference vegetation index. Bai et al. (2022) suggested that street-level green space exposure had a positive impact on active travel for university students, but there is no evidence that NDVI was related to active travel. Also, existing studies have mainly investigated the quantity of green space, while scant attention has been paid to its quality (Wang, Feng, Pearce, Zhou, et al., 2021). However, compared with quantity, the quality of green space may have a more direct impact on people's behaviour, since the quality perspective has a more direct influence on people's perceptions and preferences towards green space (B. Jiang, Larsen, Deal, & Sullivan, 2015). For instance, De Vries et al. (2013) indicated that green space quality, but not quantity, was associated with more walking or cycling as modes of transport. Traditional methods for assessing street-level green space exposure are mainly based on questionnaires (Takano, Nakamura, & Watanabe, 2002) and field audits (De Vries, Van Dillen, Groenewegen, & Spreeuwenberg, 2013), which are both high in cost and time-consuming (Wang, Lu, Wu, Liu & Yao, 2020). In recent years, street view data, along with machine learning techniques, have been widely used to assess environment exposure (Bai et al., 2022; Lu et al., 2018; Lu et al., 2019). As regards green space exposure, since street view images are usually collected on the street, new methods have been developed to assess both street-level quantity and quality using street view images (Wang, Feng, Pearce, Yao, et al., 2021).

## 3. Data and methodology

### 3.1. Data

Survey data in this study was collected in 2013 in Beijing by the research team. The primary objective of this survey was to understand the determinants of residents' quality of life in Beijing. The data was collected using a multi-stage stratified probability proportionate to population size sampling method. First, we randomly selected neighbourhoods (*shequ*) from 16 districts of Beijing. Second, we then randomly chose households from each sampled neighbourhood. Last, using the Kish Household Sampling Method (Binson & Catania, 2000), we selected one adult household member from each sampled household as the participant. Only people above 16 were invited to answer the questionnaire. Existing studies have shown that these samples were representative of the general population in Beijing based on the 2010 Census data (Wu, Wang, & Zhang, 2019a; Zhai et al., 2021). Both residential and work addresses were reported by the participants. Details of this survey can be found in previous studies (Wu et al., 2019a, 2022a; Zhai et al., 2021). After the data cleaning process (respondents with missing variables were excluded), 3099 valid respondents were included for the final analysis. Since the survey data was collected in 2013, the target subway lines also had to have been opened before 2013. Therefore, 13 subway lines (lines 1, 2, 4, 5, 6, 8, 9, 10, 13, 14, and 15, and the airport and Changping lines) and 236 stations were included in the study. Fig. 2 shows the location of participants (with random noise).

### 3.2. Variables

#### 3.2.1. Outcomes

*3.2.1.1. Transportation mode choice.* Respondents were asked to report their primary transportation mode for daily commuting (① Walking; ② Bike/motorcycle/electric bike; ③ Subway; ④ Bus; ⑤ Unit shuttle bus/unit car allocation; ⑥ Taxi; ⑦ Private car; ⑧ Others). Since we mainly focused on the effect of street-level green space around the nearest subway station, we categorized the

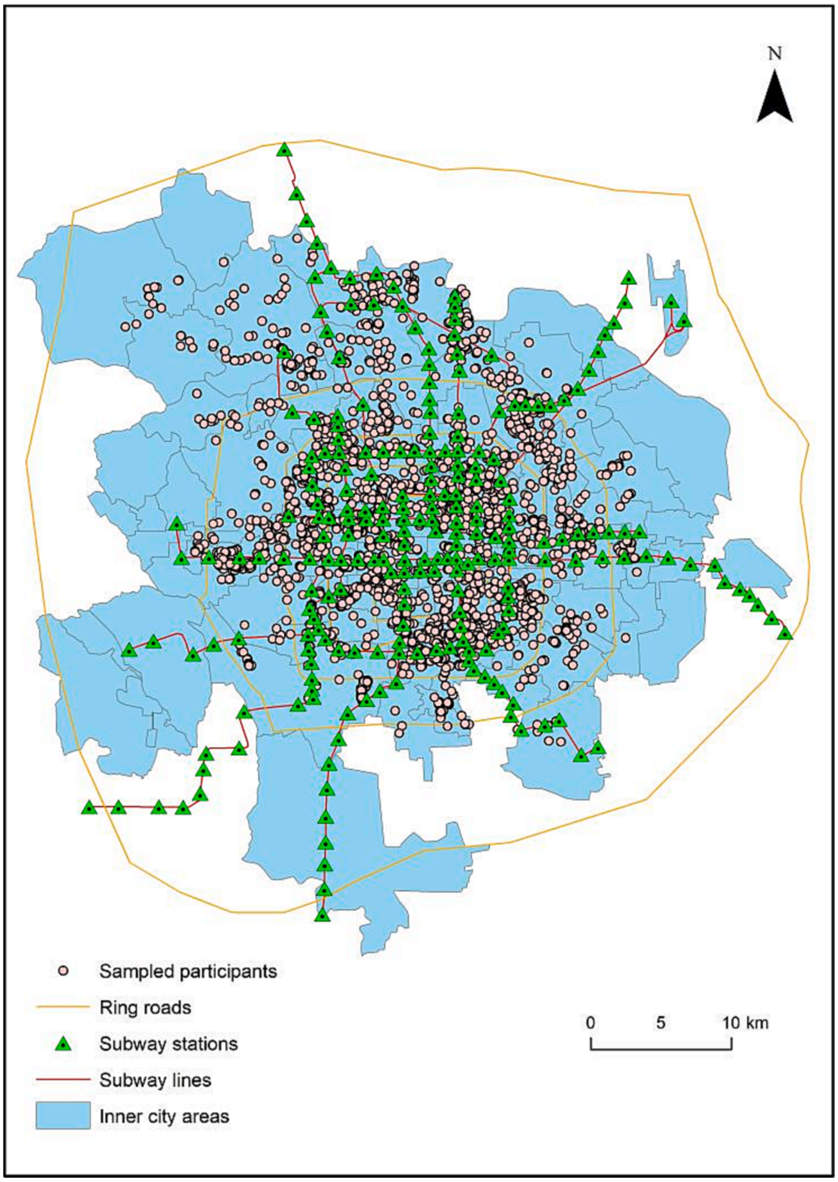


**Fig. 2.** The location of research area (with 2-5km random noise).

respondents into two groups: people who chose the subway as their primary transportation mode for daily commuting (designated as subway user = 1) and those who chose other transportation modes for daily commuting (designated as subway user = 0).

### 3.3. Travel satisfaction

Following previous studies, travel satisfaction in this study was measured using a self-reported question (De Vos & Witlox, 2017; Mouratidis, Ettema, & Næss, 2019; Zhai et al., 2021). The participants were asked 'To what extent are you satisfied with your daily travelling?'. The answers ranged from 'very dissatisfied = 1′ to 'very satisfied = 5′, so we treated it as a ordinal variable.

### 3.4. Predictors

#### 3.4.1. SVG-quality and quantity

Street view greenness quantity (SVG-quantity) around subway stations was calculated based on street view data and a machine learning technique. The street view images were downloaded in 2013 from Tencent Map [https://map.qq.com/], which has been widely used for transportation research in the Chinese context (Bai et al., 2022; R. Wang et al., 2020, 2022c, 2023). Sampling points for collecting the images were constructed along the major roads (with 100 m intervals) using OpenStreetMap (Haklay & Weber, 2008). For each sampling point, four images from the four cardinal directions were collected to reflect the street-level environment. Following previous studies, we used a fully convolutional neural network (FCN-8 s) (Long et al., 2015) along with an ADE20K (Zhou et al., 2019) training data set to extract vegetation (e.g., trees and grasses) from the images, since this method can achieve high accuracy in identifying vegetation. Both the training and testing data sets achieved high accuracy (>80%). Then, SVG-quantity per sampling point was calculated as the ratio of green space (vegetation) pixels of all four images. Last, SVG-quantity at the subway stations was the mean value of SVG-quantity of all sampling points within an 800 m circular buffer around the station.

Following existing studies (Wang et al., 2021a–c), we calculated street view greenspace quality (SVG-quality) based on street view data and a machine learning technique. We randomly selected two thousand images to construct the training data set. These images were rated based on a green space quality attributes scale (Wang, Feng, Pearce, Yao, et al., 2021; Wang, Feng, Pearce, Zhou, et al., 2021), including general impression, variation, naturalness, colourfulness, clear arrangement, shelter, absence of litter, safety, and maintenance (Cronbach's alpha > 0.80). Then, we trained a random forest (RF) model (Breiman, 2001) to predict these attributes for

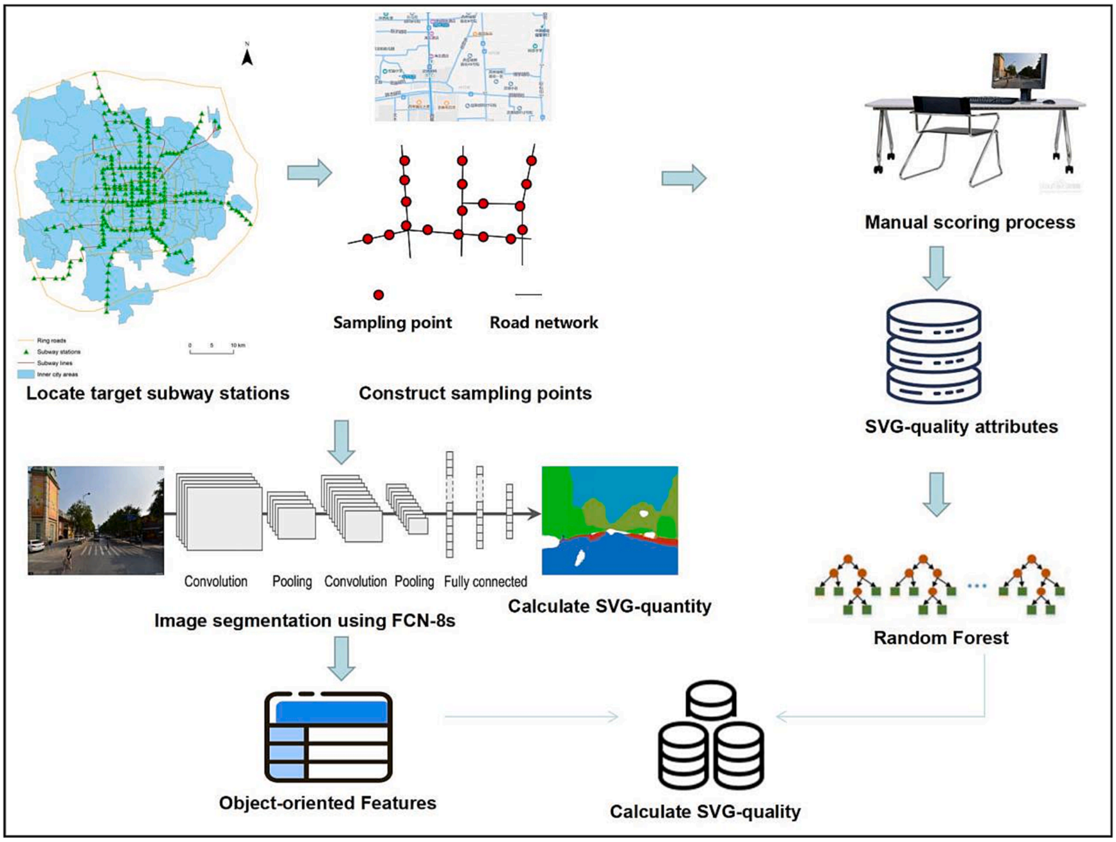


**Fig. 3.** The workflow for calculating SVG around the subway stations.

street view images. The outcomes for our RF model were green space quality attributes, while the predictors were the proportion of different objects from the image segmentation. After training, the RF model achieved high accuracy (>85%), so we then used it to predict green space quality attributes for all other images. Technical details of this approach can be found in previous studies (Wang, Feng, Pearce, Liu, et al., 2021; Wang, Feng, Pearce, Zhou, et al., 2021). The final SVG-quality for each image was the mean of all green space quality attributes. At each subway station, the SVG-quality was the mean value of all sampling points within the 800 m circular buffer. Participants' SVG-quantity and SVG-quality exposure around the subway stations was assessed based on the nearest subway station to their home address and workplace. The workflow for calculating SVG around the subway stations is shown in Fig. 3.

#### *3.4.2. Covariates*

Following previous studies (Guan & Wang, 2019a, 2019b; Smith et al., 2017), we controlled for a series of individual-level and neighbourhood-level covariates. We obtained the survey respondents' socio-demographic characteristics, including age, sex, marital status, educational attainment, monthly household income (Yuan), and car ownership. We also controlled for built environment characteristics. First, since transportation-related infrastructures play important roles in people's choice of transportation mode, the density of bus stops (number/km$^2$), and parking lots (number/km$^2$) were included. Second, based on the '3D' (density, diversity, and design) concept (Frank et al., 2006), population density (persons/km$^2$), land use mix (0–1), and intersection density (number/km$^2$) were included to reflect street-level built environments (using an 800 m circular buffer at both residential neighbourhood and workplace). Also, we included job-housing distance (m) as suggested by existing studies (Wang and Chai, 2009). Last, the accessibility of subway stations matters for people's choice as to whether or not to use the subway (H. Jiang & Levinson, 2017), so we included distance to the nearest residential subway station (m) from both respondents' residential and work contexts. Table 1 provides a summary of the variables.

**Table 1**
Descriptive statistics.

| | Proportion/Mean (SD) |
|---|---|
| Age | |
| Below 30 years | 44.89 |
| Between 30 and 50 years | 48.79 |
| Above 50 years) | 6.32 |
| Sex | |
| Male | 53.60 |
| Female | 46.40 |
| Marital status | |
| Married | 58.83 |
| Single or divorced | 41.17 |
| Educational attainment | |
| Primary school or below | 7.84 |
| High school | 24.14 |
| College or above | 68.02 |
| Monthly household income | |
| Below 10,000 Yuan | 60.50 |
| Between 10,000 and 20,000 Yuan | 31.88 |
| Above 20,000 Yuan | 7.62 |
| Car ownership | |
| Own at least one car | 36.85 |
| Otherwise | 63.15 |
| Bus stops density at residential location (numbers/km$^2$) | 18.98 (16.03) |
| Parking lots density at residential location (numbers/km$^2$) | 11.06 (18.07) |
| Population density at residential location (persons/km$^2$) | 19794.42 (8937.58) |
| Land use mix at residential location (0–1) | 0.07 (0.07) |
| Intersection density at residential location (numbers/km2) | 24.15 (9.80) |
| Bus stops density at workplace (numbers/km$^2$) | 18.68 (26.29) |
| Parking lots density at workplace (numbers/km$^2$) | 8.98 (18.37) |
| Population density at workplace (persons/km$^2$) | 20995.07 (9984.51) |
| Land use mix at workplace (0–1) | 0.22 (0.21) |
| Intersection density at workplace (numbers/km2) | 24.25(13.19) |
| Job-housing distance (m) | 4397.47(5108.41) |
| SVG-quantity for residential subway station (0–1) | 0.14 (0.06) |
| SVG-quality for residential subway station (0–1) | 0.57 (0.02) |
| SVG-quantity for workplace subway station (0–1) | 0.14 (0.05) |
| SVG-quality for workplace subway station (0–1) | 0.56 (0.02) |
| Distance to the nearest residential subway station (m) | 1093.53 (1162.63) |
| Distance to the nearest workplace subway station (m) | 991.81 (1022.80) |
| Transportation mode choice | |
| Subway | 23.04 |
| Others | 76.96 |
| Travel satisfaction (1–5) | 3.52 (0.72) |

Note: *SD* = standard deviation.

### 3.5. Statistical methods

To assess the link between street-level green space exposure around the subway station and transportation mode choice and travel satisfaction, we fitted multilevel logit and ordered logit regression (Guo & Zhao, 2000). A multilevel study design was necessary because the individuals were nested within districts. The variance inflation factors (VIF $< 3$) indicated that predictors and covariates were not multicollinear. The intra-class correlation coefficients (ICC) for the null model predicting the odds of being a subway user and reporting higher travel satisfaction at district level were 0.05 and 0.02, respectively. First, we regressed the baseline models for transportation mode choice and travel satisfaction (for subway users only) to examine the effects of covariates (Models 1 and 2). Second, we regressed the transportation mode choice on SVG around the subway station for all respondents (Models 3 to 5). Third, we regressed the travel satisfaction on SVG around the subway station for subway users (Models 6 to 8). Fourth, we regressed several regressions to test the robustness of our findings (Models 9 and 10). Last, since existing studies found that green space quality has a more significant long-term effect, while green space quantity has a more significant short-term effect (Putra, Astell-Burt, & Feng, 2022), we stratified the participants into subsamples of short-term residents (movers, defined as those who has resided in the current location for no more than five years) and long-term residents (non-movers, defined as those who has resided in the current location for more than five years) (Næss, 2009; Zhai et al., 2021) (Models 11 to 14).

## 4. Results

### 4.1. The baseline models

Model 1 (Table 2) shows the result of baseline model for the odds of being a subway user. Compared with people without a car, those owning at least one car had lower odds of being a subway user (OR. = 0.72, 95% CI = 0.58–0.90). Also, respondents with high school (OR. = 1.85, 95% CI = 1.11–3.07) educational attainment as well as respondents with college or above (OR. = 2.45, 95% CI = 1.51–3.97) educational attainment had higher odds of being a subway user. Intersection density at workplace was positively associated with the odds of being a subway user (OR. = 1.00, 95% CI = 1.00–1.01). Model 2 (Table 2) shows the result of baseline model for the travel satisfaction of subway user.

Model 2 (Table 2) shows the result of baseline model for the travel satisfaction of subway user. Subway users with household income between 10,000 and 20,000 Yuan had higher travel satisfaction than those with household income below10000 Yuan (OR. = 1.33, 95% CI = 1.13–1.56). Compared with subway users without a car, those owning at least one car had lower travel satisfaction (OR. = 0.80, 95% CI = 0.68–0.93). Population density at residential location (OR. = 1.00, 95% CI = 1.00–1.00), intersection density at residential location (OR. = 1.01, 95% CI = 1.00–1.03), parking lots density at workplace (OR. = 1.00, 95% CI = 1.00–1.01) was

**Table 2**
Baseline models.

| | Model 1 OR. (95% CI) | Model 2 OR. (95% CI) |
|---|---|---|
| Age between 30 and 50 years (referenced group = Age below 30 years) | 0.79(0.61–1.02) | 1.02(0.85–1.24) |
| Age above 50 years (referenced group = Age below 30 years) | 0.77(0.48–1.23) | 1.20(0.87–1.66) |
| Male (referenced group = Female) | 0.88(0.73–1.06) | 1.10(0.96–1.26) |
| Married (referenced group = Single or divorced) | 0.85(0.65–1.09) | 1.05(0.87–1.27) |
| High school (referenced group = Primary school or below) | 1.85**(1.11–3.07) | 1.00(0.75–1.32) |
| College or above (referenced group = Junior high school or below) | 2.45*** (1.51–3.97) | 1.02(0.78–1.33) |
| Household income between 10,000 and 20,000 Yuan (referenced group = Household income below 10,000 Yuan) | 1.16(0.94–1.44) | 1.33*** (1.13–1.56) |
| Household income above 20,000 Yuan (referenced group = Household income below 10,000 Yuan) | 0.96(0.65–1.41) | 1.27*(0.96–1.69) |
| Own at least one car (referenced group = Otherwise) | 0.72*** (0.58–0.90) | 0.80*** (0.68–0.93) |
| Bus stops density at residential location | 0.99(0.98–1.00) | 1.00(0.99–1.00) |
| Parking lots density at residential location | 1.00(0.99–1.00) | 0.99(0.99–1.00) |
| Population density at residential location | 1.00(0.99–1.00) | 1.00*** (1.00–1.00) |
| Land use mix at residential location | 0.06(0.00–1.92) | 0.44(0.06–3.01) |
| Intersection density at residential location | 1.00(0.98–1.02) | 1.01**(1.00–1.03) |
| Bus stops density at workplace | 0.99(0.99–1.00) | 0.99(0.99–1.00) |
| Parking lots density at workplace | 0.99(0.99–1.00) | 1.00**(1.00–1.01) |
| Population density at workplace | 0.99(0.99–1.00) | 0.99**(0.99–0.99) |
| Land use mix at workplace | 1.30(0.48–3.48) | 0.67(0.36–1.26) |
| Intersection density at workplace | 1.00*** (1.00–1.01) | 0.99**(0.99–0.99) |
| Job-housing distance | 1.00(1.00–1.00) | 0.99*(0.99–1.00) |
| Log likelihood | −1400.21 | −3309.91 |
| AIC | 2844.43 | 6669.82 |

Note: OR = odds ratio; 95% CI = 95% confidence interval; AIC = Akaike information criterion. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Dependent variable in Model 1 is transportation mode (subway user), and dependent variable in Model 2 is travel satisfaction.

positively associated with travel satisfaction of subway user, while population density at workplace (OR. = 0.99, 95% CI = 0.99–0.99) and intersection density at workplace (OR. = 0.99, 95% CI = 0.99–0.99) was negatively associated with travel satisfaction of subway user.

### 4.2. The associations between street-level green space exposure around the subway station and transportation mode choice

Model 3 to 5 (Table 3) present the associations between street-level green space exposure around the subway station and transportation mode choice. The results indicate that there is no evidence that either SVG-quantity (OR. = 0.94, 95% CI = 0.06–2.23) or SVG-quality (OR. = 1.58, 95% CI = 0.38–2.73) for residential subway station was associated with odds of being a subway user. Also, SVG-quantity (OR. = 6.13, 95% CI = 1.75–7.32) but not SVG-quality (OR. = 0.86, 95% CI = 0.31–1.77) for workplace subway station was positively associated with odds of being a subway user. Both distance to the nearest residential subway station (OR. = 0.99, 95% CI = 0.99–0.99) and distance to the nearest workplace subway station (OR. = 0.99, 95% CI = 0.99–0.99) were negatively associated with odds of being a subway user.

### 4.3. The associations between street-level green space exposure around the subway station and travel satisfaction

Model 6 to 8 (Table 4) present the associations between street-level green space exposure around the subway station and travel satisfaction. The results indicate that SVG-quality for residential subway station (OR. = 0.82, 95% CI = 0.02–1.59) but not workplace subway station (OR. = 2.45, 95% CI = 1.21–3.59) was positively associated with odds of reporting higher travel satisfaction for subway user. However, there is no evidence that either SVG-quantity for residential subway station (OR. = 1.54, 95% CI = 0.13–3.37) or workplace subway station (OR. = 1.47, 95% CI = 0.16–2.70) was associated with travel satisfaction for subway user. Also, distance to the nearest residential subway station (OR. = 0.99, 95% CI = 0.99–1.00) but not distance to the nearest workplace subway station (OR. = 0.99, 95% CI = 0.99–1.00) was negatively associated with odds of reporting higher travel satisfaction for subway user.

### 4.4. Sensitivity analysis

Then, we reran several models as sensitivity analysis to test the robustness of findings (Table 5: Models 9 and 10). First, we used 600-m (rather than 800-m) circular buffer and re-ran the models (Model 9a and 10a). Second, we used 1000-m (rather than 800-m) circular buffer and re-ran the models (Model 9b and 10b). Third, since both subway and bus are public transportation, they may be substitutable for each other (C. Liu & Li, 2020). We excluded bus user and re-ran the regression (Model 9c). Last, we changed Travel satisfaction into a binary variable ('satisfied' and 'very satisfied' = 1) and re-ran a multilevel logit regression (Model 10c). Despite some differences in magnitude, the SVG - transportation mode choice and SVG - travel satisfaction associations remained the same across all models.

### 4.5. Comparison for the effect of street-level green space exposure around the subway station between movers and non-movers

Model 11 (Table 6) presents the associations between street-level green space exposure around the subway station and transportation mode choice for movers. The results indicated that there is no evidence that either SVG-quantity (OR. = 0.78, 95% CI = 0.02–1.87) or SVG-quality (OR. = 1.14, 95% CI = 0.21–2.19) for residential subway station was associated with odds of being a subway user. Also, SVG-quantity (OR. = 3.09, 95% CI = 1.36–6.16) but not SVG-quality (OR. = 0.55, 95% CI = 0.20–2.42) for workplace subway station was positively related to odds of being a subway user. Distance to the nearest workplace subway station (OR. = 0.99, 95% CI = 0.99–0.99) but not distance to the nearest residential subway station (OR. = 0.99, 95% CI = 0.99–1.00) was negatively related to odds of being a subway user. Model 12 (Table 6) presents the associations between street-level green space exposure around the subway station and transportation mode choice for non-movers. The results indicated that SVG-quality (OR. = 1.32, 95% CI = 1.08–2.61) but not SVG-quantity (OR. = 0.82, 95% CI = 0.03–2.48) for residential subway station was positively associated with odds of being a subway user. Also, SVG-quantity (OR. = 4.55, 95% CI = 1.44–6.26) but not SVG-quality (OR. = 0.40,

**Table 3**
The associations between street-level green space exposure around the subway station and transportation mode choice.

| | Model 3<br>OR. (95% CI) | Model 4<br>OR. (95% CI) | Model 5<br>OR. (95% CI) |
|---|---|---|---|
| SVG-quantity for residential subway station | 0.81(0.11–3.64) | | 0.94 (0.06–2.23) |
| SVG-quality for residential subway station | 1.14(0.43–2.29) | | 1.58 (0.38–2.73) |
| SVG-quantity for workplace subway station | | 3.57** (1.20–5.84) | 6.13** (1.75–7.32) |
| SVG-quality for workplace subway station | | 0.57 (0.30–2.23) | 0.86(0.31–1.77) |
| Distance to the nearest residential subway station | 0.99*** (0.99–0.99) | | 0.99*** (0.99–0.99) |
| Distance to the nearest workplace subway station | | 0.99*** (0.99–0.99) | 0.99*** (0.99–0.99) |
| Log likelihood | −1388.11 | −1378.43 | −1371.29 |
| AIC | 2826.23 | 2806.876 | 2798.599 |

Note: Models are adjusted for all confounders. DV = dependent variable; OR = odds ratio; 95% CI = 95% confidence interval; AIC = Akaike information criterion. *p < 0.10, **p < 0.05, ***p < 0.01. Dependent variable in Model 3, 4 and 5 is transportation mode (subway user).

**Table 4**
The associations between street-level green space exposure around the subway station and travel satisfaction.

| | Model 6<br>OR. (95% CI) | Model 7<br>OR. (95% CI) | Model 8<br>OR. (95% CI) |
|---|---|---|---|
| SVG-quantity for residential subway station | 0.99(0.05–1.37) | | 0.82 (0.02–1.59) |
| SVG-quality for residential subway station | 2.26** (1.36–3.62) | | 2.45** (1.21–3.59) |
| SVG-quantity for workplace subway station | | 1.58 (0.07–3.17) | 1.54 (0.13–3.37) |
| SVG-quality for workplace subway station | | 1.81(0.65–2.34) | 1.47(0.16–2.70) |
| Distance to the nearest residential subway station | 0.99** (0.99–0.99) | | 0.99*(0.99–1.00) |
| Distance to the nearest workplace subway station | | 0.99 (0.99–1.00) | 0.99(0.99–1.00) |
| Log likelihood | −3304.11 | −3306.20 | −3302.50 |
| AIC | 6664.22 | 6668.40 | 6667.01 |

Note: Models are adjusted for all confounders. DV = dependent variable; OR = odds ratio; 95% CI = 95% confidence interval; AIC = Akaike information criterion. *p < 0.10, **p < 0.05, ***p < 0.01. Dependent variable in Model 6, 7 and 8 is travel satisfaction.

**Table 5**
Sensitivity analysis.

| | Model 9a<br>OR. (95% CI) | Model 9b<br>OR. (95% CI) | Model 9c<br>OR. (95% CI) |
|---|---|---|---|
| SVG-quantity for residential subway station | 0.77(0.03–2.47) | 0.71(0.04–2.42) | 0.63(0.03–2.20) |
| SVG-quality for residential subway station | 1.17(0.31–2.84) | 1.29(0.38–3.29) | 1.48(0.29–3.20) |
| SVG-quantity for workplace subway station | 3.84** (1.88–6.61) | 3.54**(1.41–6.46) | 2.94**(1.50–5.33) |
| SVG-quality for workplace subway station | 0.50(0.28–2.29) | 0.54(0.35–2.50) | 0.42(0.20–1.92) |
| Distance to the nearest residential subway station | 0.99***(0.99–0.99) | 0.99***(0.99–0.99) | 0.99*(0.99–1.00) |
| Distance to the nearest workplace subway station | 0.99***(0.99–0.99) | 0.99***(0.99–0.99) | 0.99***(0.99–0.99) |
| Log likelihood | −1366.88 | −1403.17 | −1083.60 |
| AIC | 2789.77 | 2862.35 | 2221.20 |
| | Model 10a<br>OR. (95% CI) | Model 10b<br>OR. (95% CI) | Model 10c<br>OR. (95% CI) |
| SVG-quantity for residential subway station | 0.76(0.02–1.48) | 0.77(0.01–2.04) | 0.76(0.04–2.61) |
| SVG-quality for residential subway station | 1.53**(1.30–2.94) | 1.48**(1.18–2.78) | 1.55** (1.16–2.30) |
| SVG-quantity for workplace subway station | 1.29(0.03–3.35) | 1.35(0.06–3.56) | 1.41(0.04–2.78) |
| SVG-quality for workplace subway station | 1.63 (0.35–3.11) | 1.64(0.31–3.31) | 1.54(0.27–3.79) |
| Distance to the nearest residential subway station | 0.99*(0.99–1.00) | 0.99*(0.99–1.00) | 0.99(0.99–1.00) |
| Distance to the nearest workplace subway station | 0.99(0.99–1.00) | 0.99(0.99–1.00) | 0.99(0.99–1.00) |
| Log likelihood | −3285.50 | −3358.61 | −2076.95 |
| AIC | 6633.01 | 6779.225 | 4209.90 |

Note: Models are adjusted for all confounders. DV = dependent variable; OR = odds ratio; 95% CI = 95% confidence interval; AIC = Akaike information criterion. *p < 0.10, **p < 0.05, ***p < 0.01. Dependent variable in Model 9 is transportation mode (subway user), and dependent variable in Model 10 is travel satisfaction.

**Table 6**
The associations between street-level green space exposure around the subway station and travel satisfaction (Movers vs. Non-movers).

| | Model 11 (Movers)<br>OR. (95% CI) | Model 12 (Non-movers)<br>OR. (95% CI) | Model 13 (Movers)<br>OR. (95% CI) | Model 14 (Non-movers)<br>OR. (95% CI) |
|---|---|---|---|---|
| SVG-quantity for residential subway station | 0.78(0.02–1.87) | 0.82(0.03–2.48) | 0.70(0.04–1.96) | 0.81(0.04–1.48) |
| SVG-quality for residential subway station | 1.14(0.21–2.19) | 1.32**(1.08–2.61) | 1.18(0.88–2.40) | 1.24**(1.09–3.37) |
| SVG-quantity for workplace subway station | 3.09**(1.36–6.16) | 4.55**(1.44–6.26) | 2.26(0.01–3.01) | 1.95(0.07–3.29) |
| SVG-quality for workplace subway station | 0.55(0.20–2.42) | 0.40(0.18–2.09) | 1.24(0.25–2.94) | 1.65(0.28–2.18) |
| Distance to the nearest residential subway station | 0.99* (0.99–1.00) | 0.99***(0.99–0.99) | 0.99(0.99–1.00) | 0.99* (0.99–1.00) |
| Distance to the nearest workplace subway station | 0.99** (0.99–0.99) | 0.99***(0.99–0.99) | 1.00(0.99–1.00) | 0.99 (0.99–1.00) |
| Log likelihood | −350.95 | −1007.63 | −801.20 | −2478.68 |
| AIC | 755.90 | 2071.27 | 1664.41 | 5019.36 |

Models are adjusted for all confounders. OR = odds ratio; 95% CI = 95% confidence interval; AIC = Akaike information criterion. Dependent variable in Model 11 and 12 is transportation mode (subway user), and dependent variable in Model 13 and 14 is travel satisfaction.

95% CI = 0.18–2.09) for workplace subway station was positively related to odds of being a subway user. Both distance to the nearest residential subway station (OR. = 0.99, 95% CI = 0.99–0.99) and distance to the nearest workplace subway station (OR. = 0.99, 95% CI = 0.99–0.99) were negatively related to odds of being a subway user.

Model 13 (Table 6) presents the associations between street-level green space exposure around the subway station and travel satisfaction for movers. The results indicated that neither SVG-quantity (OR. = 0.70, 95% CI = 0.04–1.96) nor SVG-quality (OR. = 1.18, 95% CI = 0.88–2.40) for residential subway station was associated with travel satisfaction. Also, there is no evidence either SVG-quantity (OR. = 2.26, 95% CI = 0.01–3.01) or SVG-quality (OR. = 1.24, 95% CI = 0.25–2.94) for workplace subway station was associated with travel satisfaction. Neither distance to the nearest residential subway station (OR. = 0.99, 95% CI = 0.99–1.00) nor distance to the nearest workplace subway station (OR. = 1.00, 95% CI = 0.99–1.00) was related to travel satisfaction. Model 14 (Table 6) presents the associations between street-level green space exposure around the subway station and travel satisfaction for non-movers. The results indicated that only SVG-quality (OR. = 1.24, 95% CI = 1.09–3.37) but not SVG-quantity (OR. = 0.81, 95% CI = 0.04–1.48) for residential subway station was positively associated with travel satisfaction. Also, there is no evidence either SVG-quantity (OR. = 1.95, 95% CI = 0.07–3.29) or SVG-quality (OR. = 1.65, 95% CI = 0.28–2.18) for workplace subway station was associated with travel satisfaction. Neither distance to the nearest residential subway station (OR. = 0.99, 95% CI = 0.99–1.00) nor distance to the nearest workplace subway station (OR. = 0.99, 95% CI = 0.99–1.00) was related to travel satisfaction.

## 5. Discussion

In this study, we systematically investigated the relationship between street-level green space exposure and transportation mode choice (whether to be a subway user)/travel satisfaction in both residential and workplace neighbourhoods. We contributed to the existing literature in several aspects. First, we paid attention to the effects of street-level green space around major transportation infrastructures rather than people's home addresses. The most important finding in this study is that there is evidence that green space exposure at subway stations is associated with transportation mode choice and travel satisfaction. One possible explanation is that existing studies have found that economic activities are quite prosperous around the subway stations, which means travellers can easily find target locations around the subway stations (Gao et al., 2018). In addition, subway stations are important locations for the interchange of different transportation modes such as free-floating bikes (Chen et al. 2022; Chen et al., 2023). Therefore, a greener environment around the subway stations can provide people with a better experience when traveling around the sites, which may encourage the use of subway and travel satisfaction of subway users. Second, we considered both the residential context and the work context, which are both important for transportation-related behaviours. Third, we stratified the participants into subsamples of movers and non-movers to investigate the long-term and short-term effects of street-view green space. Last, we used street view data and a machine learning approach to measure street-level green space around the subway station, which can reflect people's visual environment exposure and has an influence on their environmental perception.

The results indicated that SVG-quantity for workplace subway stations, but not for residential neighbourhood subway stations, was positively related to the odds of being a subway user. There are several explanations for this finding. First, since most people work start early in the morning, people usually have to rush from home to the workplace and feel stressed before work (Sun, Lin, & Yin, 2021). Therefore, when choosing a transportation mode, people may focus more on how to reach the workplace on time, rather than paying attention to the surrounding environment at the residential neighbourhood's transit station (Sun et al., 2021). After work, people may have less working pressure and may not be in a hurry to go back home when choosing a transportation mode (Wu, Wang, & Zhang, 2019b), so they are more likely to pay more attention to the surrounding environment around the transit station. Second, existing studies have pointed out that the time at which people finish work varies more significantly than the time at which they start work (Shen, Chai, & Kwan, 2015). Hence, since Beijing has a large population, people are more likely to suffer from crowded transportation before work, while they may be less influenced by this factor after work and may focus more on the environment surrounding the transit station (Mao, Ettema, & Dijst, 2016). Last, most of Beijing's job opportunities are in the city centre, and the density of transit stations for public transportation is high in this area (Huang, Levinson, Wang, & Jin, 2019; Zhao, Lü, & De Roo, 2011). Therefore, the environment surrounding the subway station at people's workplace can encourage people to walk from the workplace to the station and thus improve subway use (Yang et al., 2022). However, residential neighbourhoods in Beijing are distributed more diffusely than job locations (Huang et al., 2019), and their surrounding transit stations may not be dense enough to encourage residents to use them when travelling from home. Under such circumstances, the environment surrounding the subway stations in people's residential neighbourhoods may not matter for their choice of transportation mode. However, SVG-quality for residential neighbourhood subway stations, but not for workplace subway stations, was positively related to the odds of being a subway user only for non-movers, while there is no evidence that SVG-quality was related to the odds of being a subway user for movers. A possible explanation for this is that compared with green space quantity, it takes more time for green space quality to take effect, since the quantity perspective (e.g., greenness) is directly perceived (Putra et al., 2022). Hence, the decision on transportation mode is more of a direct and momentary process for movers (Meixell & Norbis, 2008), while non-movers have resided longer in the current location and have been influenced by the long-term effect of green space, and thus may be more influenced by green space quality (Putra et al., 2022). Another explanation is that existing evidence has suggested that those who have recently moved in have a higher expectation for green space quality than local residents, since they may have paid more to move to the current location (Xiao, Lu, Guo, & Yuan, 2017). Therefore, green space quality around the subway station may not reach the required threshold to reveal a significant impact on movers' choice of transportation mode in this study.

Our findings also indicated that SVG-quality for residential subway stations, but not for workplace subway stations, was positively associated with travel satisfaction only for non-movers. Since non-movers are more influenced by the long-term effect of local environment exposure due to longer residency (Zhai et al., 2021), our findings again confirmed that green space quality may have a more long-term effect than green space quality on transportation-related behaviour. There are several explanations for the inconsistent findings between residential and work contexts. First, previous studies have pointed out that the quality perspective contributes more to the restorative effects of green space than the quantity perspective, since the quality perspective is directly associated with the attractiveness of green space features (Liu, Qu, Ma, Wang, & Qu, 2022). As mentioned above, people are more likely to be stressed before work than after work, and existing literature has shown that the restorative effect of green space is more pronounced when people are under pressure (Van den Berg, Jorgensen, & Wilson, 2014). Therefore, people may enjoy a greater restorative effect of green space around subway stations in the residential neighbourhood context than in the workplace. Second, subway stations in residential areas are usually more crowded due to more consistent start times, which means that people may have to wait in a queue before entering the station (J. Huang et al., 2019). Hence, the restorative effect of green space quality is positively associated with exposure time (Van den Berg et al., 2014). This indicates that subway users may have a longer duration of exposure to the environment surrounding residential subway stations, and thus may be more influenced by the green space exposure in such contexts. Third, when people need to commute by subway after work in China, it is usually after 6 p.m. and might already be dark outside (Wu, Chen, Stephens, & Liu, 2019). Subway users at the workplace may not be able to view the quality attributes of green space clearly under such circumstances and have higher travel satisfaction, since the restorative effects of green space quality mainly come through its visual effect (Liu et al., 2022). Last, our results showed that green space quality is higher in residential subway stations than that in those near the workplace, so it is likely that green space quality in the workplace is not high enough to trigger a significant restorative effect on subway users. However, there is no evidence that SVG-quantity was related to travel satisfaction for subway users. A possible explanation is that green space quantity reflects an objective level of greenness, while travel satisfaction is the individual's subjective feeling. Therefore, the subway users in this study were not influenced by green space quantity, since they may not be sensitive to the level of green space quantity or not connected to natural elements. Another possible explanation is that the dose–response effect of green space quantity on landscape preference (Jiang et al., 2015) implies that the green space quantity around the subway station in this study may not be high enough to attract subway users' attention.

### 5.1. Limitations

Our study is not without limitations. First, the cross-sectional data design in this study prevents us from inferring causation between green space exposure and transportation mode choice/travel satisfaction. Second, most of the variables were self-reported and may be influenced by measurement bias. Only one item was used to measure travel satisfaction, and it may be too simple to reflect people's general travel satisfaction (Gao et al., 2022). Also, respondents' workplaces were also self-reported, which may lead to bias when geographically coding this variable using ArcGIS software. Third, although we tested different circular buffer sizes around subway stations for sensitivity analysis, our results may still be influenced by the Modifiable Areal Unit Problem (Fotheringham & Wong, 1991). Fourth, the presence of subway stations is only a very small part of subway travel, and the green space cannot be felt during the subway travel process. Therefore, the association between green space and subway travel choice and satisfaction may be biased. Last, our street view images may be unable to reflect seasonal fluctuations of the local vegetation in Beijing, so our results may be influenced by seasonal changes in the greenness of vegetation. Also, our data was collected in 2013, and the COVID-19 pandemic has changed people's use of public transit (Qi et al., 2021), so some of our results may not be applicable in the post-COVID-19 pandemic period.

### 5.2. Policy implications

Our findings have important implications for promoting the use of public transportation. Overall, machine learning and street image data can be used to better support spatial–temporal impact assessment of transportation infrastructure and develop a resilient and sustainable transportation infrastructure. First, street-level green space exposure around subway stations is important for encouraging people to take the subway, so more plants such as trees and grasses should be planned around the major subway stations, especially in urban areas. Also, since the quality of street-level green space plays an important role in improving subway users' travel satisfaction, it is important for the government to invest in maintaining the green space around the stations, which can improve people's general impression of green space. Second, since a particular subway line serves the function across different contexts, and the effect of SVG vary across different contexts, it is important to identify whether a subway station is in the residential area or the workplace. For example, existing studies have suggested that mobile phone data can be used to distinguish between residential and business areas (Zhou et al., 2018), and such information can help policymakers decide whether they should prioritize SVG quantity or quality around a specific station. Third, street-level green space quantity is important for influencing both movers and non-movers' use of the subway, while street-level green space quality is more important for non-movers' use of the subway and travel satisfaction. Therefore, the policy should be more targeted across different areas. For instance, if areas have large numbers of new movers (e.g., city centre) who have just moved in, then the priority should be to improve the quantity of green space around the stations. However, if an area has fewer movers, then the priority should be to improve the quality of green space around the stations to improve viscosity for subway users. Last, we also found that the accessibility of subway stations is important in both residential and work contexts, so it is necessary to solve the 'last mile problem' (Song, Cherrett, McLeod, & Guan, 2009) to help people get to the station more easily. For example, more public bikes should be provided around subway stations to help people get to their destinations from the station.

## 6. Conclusion

Using street view data and a machine learning technique, we examined the effect of street-level green space exposure around subway stations on transportation mode choice and travel satisfaction, paying special attention to the difference between residential and work contexts. The results suggested that SVG-quantity for workplace subway stations was positively related to the odds of being a subway user for both non-movers and movers. However, SVG-quality for residential subway stations was positively related to the odds of being a subway user only for non-movers. Also, SVG-quality for residential subway stations was positively associated with travel satisfaction only for non-movers. Our findings provide evidence that green space around the subway stations in both residential neighbourhoods and workplaces should be considered simultaneously in public policies and interventions.

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## CRediT authorship contribution statement

**Wenjie Wu:** Funding acquisition, Project administration, Resources, Supervision, Conceptualization, Writing – review & editing. **Yao Yao:** Data curation, Methodology. **Ruoyu Wang:** Conceptualization, Data curation, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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