Received: 12 December 2021 | Revised: 1 April 2022 | Accepted: 25 July 2022

DOI: 10.1111/hsc.13968

ORIGINAL ARTICLE

Health and Social Care in the community

WILEY

Exploring the association between neighbourhood streetscape vegetation and subjective well-being in a high-density built environment: Evidence from Beijing, China

Ruoyu Wang PhD[1] | Linchuan Yang PhD[2] | Yao Yao PhD[3,4] | Wenjie Wu PhD[5]

[1]UKCRC Centre of Excellence for Public Health/Centre for Public Health, Queen's University Belfast, Belfast, UK

[2]Department of Urban and Rural Planning, School of Architecture and Design, Southwest Jiaotong University, Chengdu, China

[3]School of Geography and Information Engineering, China University of Geosciences, Wuhan, China

[4]Center for Spatial Information Science, The University of Tokyo, Chiba, Japan

[5]School of Urban Design, Wuhan University, Wuhan, China

Correspondence
Wenjie Wu, School of Urban Design, Wuhan University, Wuhan, China.
Email: caswwj@foxmail.com

Funding information
National Natural Science Foundation of China, Grant/Award Number: 41801306 and 41971194; National Office for Philosophy and Social Sciences, Grant/Award Number: 20ZDA037; Fundamental Research Funds for the Central Universities, Grant/Award Number: 21621105; Outstanding Innovative Talents Cultivation Funded Programs for Doctoral Students of Jinan University, Grant/Award Number: 2021CXB013; Open Fund of State Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Grant/Award Number: 18S01

Abstract

Many studies have disentangled the perceived benefits of vegetation on subjective well-being (SWB). Yet, scant attention has been paid to the joint effect of vegetation and building density on SWB. This study explores the relationship between streetscape vegetation (SV), building density and SWB in Beijing, China. Our analysis relies on rich measures of street view data to assess SV exposure at the neighbourhood level. Notably, we distinguish between trees (SV-tree) and grasses (SV-grass) when evaluating SV metrics. The results suggest that streetscape trees and grasses are positively associated with SWB, though estimated effects are dependent upon tree and grass density exposures. We also find that the effects of streetscape trees and grass are moderated by building density in the neighbourhood. Additional decomposition analysis provides the insight that the well-being implications of street vegetation and building density are varied significantly by individual sociodemographic characteristics such as sex, age and income. The findings of this study suggest the importance of considering density in SV planning and land use policies to enhance people's quality of life.

KEYWORDS
density, modified effect, street view data, streetscape vegetation, subjective well-being

1 | INTRODUCTION

Exposure to the urban vegetation (greenspace) is beneficial to residents' well-being (Chan & Liu, 2018; Liu, Wang, et al., 2020; Sarkar et al., 2018; Song et al., 2020; Ugolini et al., 2021; Wang & Lan, 2019; Wu et al., 2021; Xie et al., 2018; Zhong et al., 2020) through several underlying channels at work such as facilitating capacities, preventing pollution harms and restoring capacities (Markevych et al., 2017; Nieuwenhuijsen et al., 2017). First, urban vegetation can not only encourage residents to take more physical activity but also increase their neighbourhood social cohesion, both of which are beneficial for well-being (Guo et al., 2021; Mao et al., 2021; Sugiyama et al., 2008; Wang et al., 2019). Second, previous studies pointed out that urban vegetation can prevent the negative effect of pollution harms such as heat (Son et al., 2016), noise (Jang et al., 2015), and air pollution (Jiang et al., 2019; Wang et al., 2019). Last, urban vegetation also helps residents restore their capacities due to its restorative features such as compatibility and fascination (Kaplan, 2001). In recent years, some studies found that different urban vegetation (i.e. trees vs. grasses) may have different impacts on residents' well-being (Astell-Burt & Feng, 2019; Reid et al., 2017; Wang et al., 2019). For example, Astell-Burt and Feng (2019) found that the tree canopy is associated with better mental well-being and health, whilst exposure to grass is associated with higher prevalent psychological distress. Reid et al. (2017) pointed out that tree density is related to better self-reported health, but grass density is not. Wang et al. (2019) indicated that streetscape trees and grasses benefit mental health through several mechanisms (e.g. decreasing perceived and objectively measured air pollution).

Street vegetation has been recognised as an important form of urban vegetation for influencing residents' well-being (Liu, Wang, et al., 2020; Liu, Zhang, et al., 2020; Wang et al., 2019). Yet, it has received less attention than other large green infrastructures such as parks due to data and methodological limitations (Wang et al., 2019). Also, whether different types of street vegetation (e.g. trees vs. grasses) may have heterogeneous effects on well-being is still unclear (Wang et al., 2019). Most previous studies assess street vegetation through remote sensing images (Li et al., 2016) or field audit (Sugiyama et al., 2008). Remote sensing images can provide the distribution of street vegetation on a large scale, but it usually does not include small street vegetation and may not be applied for places where high-resolution remote sensing images are unavailable (Wang et al., 2019). On the contrary, the field audit method can include small street vegetation, but it is usually time-consuming and labour-intensive which prevents it from being applicable to a large study area (Wang et al., 2019). In recent years, more and more studies begin to use street view images along with machine learning methods for assessing street vegetation (Li et al., 2016; Liu et al., 2019). This new method is more efficient than field audit and can include more small street vegetation than remote sensing images. Hence, it can also identify different street vegetation (i.e. grasses and trees) with an appropriate training dataset, so it may be a better method for assessing street vegetation than remote sensing images and field audits, especially in a large and dense neighbourhood.

Building density is an important component of the neighbourhood environment in influencing residents' well-being (Perini & Magliocco, 2014). There is a growing awareness amongst scholars that living in a neighbourhood with higher building density may have influence on residents' well-being through several pathways (Chan & Liu, 2018). First, building density may increase pollution harms such as heat, noise and air pollution within the neighbourhood which are all harmful to residents' well-being (Guedes et al., 2011; Niachou et al., 2008). For example, high neighbourhood building density may block the wind and lower its speed, resulting in the heat island effect which increases the temperature (Mirzaei et al., 2012). Hence, high neighbourhood building density also increases the level of atmospheric pollutants, since it has influence on the shape of the street canyon and the dispersion of atmospheric pollutants (Theodoridis & Moussiopoulos, 2000). The second domain of pathway linking building density to well-being is associated with the use of open-space (Azad et al., 2018). Residents living in high neighbourhood building density have less public openspace which may decrease their outdoor physical activity and increase the prevalence of different kinds of chronic diseases (Azad et al., 2018). The last domain of the pathway is associated with the mental stress caused by crowding (Ho et al., 2008; Saarloos et al., 2011; Wiesenfeld, 1987; Xue et al., 2016). A plethora of studies has documented that living in a crowded environment may increase residents' anxiety and depression since they get less private space and more feeling of tension in a dense environment (Saarloos et al., 2011).

Our research has four contributions. First, this study adds to the literature on the association between streetscape vegetation (SV) and subjective well-being (SWB) and further distinguishes the effect of different SV (grasses vs. tresses). Most previous studies measured urban vegetation (greenspace) based on satellite images (Li et al., 2016). However, recent studies showed that this method may ignore the effect of street-level small vegetation (Li et al., 2016). Therefore, our research can improve our understanding of vegetation-SWB association by further taking SV into account. Second, it enhances our knowledge of the building density-SWB association in developing countries. Taking a dense city in China as an example, this study measures building density based on the plot ratio. In China, due to the rapid urbanisation, the population has increased dramatically in a metropolis such as Beijing and Shanghai (Zhang & Song, 2003). Therefore, the building and population density in China's metropolitan areas (e.g. Beijing) is much larger than in most western countries. Third, it further identifies the joint effect of both SV and building density on SWB. Whilst a plethora of studies has disentangled the independent effect of vegetation on well-being, scant attention has been paid to the modified effect of building density (He et al., 2022). A recent

What is known about this topic?

- Green space serves as an important factor in relation to subjective well-being.
- The association between green space and subjective well-being varies across different neighbourhood contexts.
- In previous studies, general green space were researched in higher proportions, whilst streetscape vegetation received less attention.

What this paper adds?

- Both streetscape trees and grasses are positively associated with subjective well-being.
- The association between streetscape vegetation and subjective well-being is moderated by building density.
- The effect of streetscape vegetation is more beneficial for disadvantaged groups.

study found that the effect of greenspace on life satisfaction is moderated by urban density, since people's use of greenspace may vary across different density contexts (He et al., 2022). This is particularly important in the Chinese context, where neighbourhood building density is extremely high. Last, heterogeneous effects of different socioeconomic levels for different SV (grasses vs. tresses) are also explored.

2 | METHODOLOGY

2.1 | Data

This study was based on the data of a survey conducted in 2013 in Beijing. The data were collected using a multi-stage stratified PPS (probability proportionate to population size) sampling method. First, residential neighbourhoods from the districts of Beijing were selected (Figure S1). Second, sampled households from each neighbourhood were chosen. Last, we randomly chose one adult household member from each household based on the Kish Grid method as a respondent. Recent studies have shown that the respondents in this survey are representative of the population in Beijing based on census data (Wu, Chen, et al., 2020; Wu, Dong, et al., 2020). The survey yielded a total of 5105 valid respondents.

2.2 | Dependent variable

Following previous studies (Campbell et al., 1976), SWB in this study was measured by a single question. The respondents were asked 'how do you feel about the current state of your life'. The answered item was scored using a five-point scale '1 = very unhappy, 2 = unhappy, 3 = general, 4 = happy, 5 = very happy'. We regarded 'very unhappy' and 'unhappy' as low SWB whilst 'general', 'happy' and 'very happy' were regarded as high SWB. We did not treat it as an ordinal variable, since using ordinal logistic regression usually violates the parallel lines assumption (Agresti, 2003).

2.3 | Independent variable

2.3.1 | Streetscape trees and grass exposure

We used street view images to assess neighbourhood streetscape greenness exposure. We collected the street view image from Tencent Map following previous studies (Wang et al., 2019, 2021). Street view sampling points were constructed 100-m apart based on the road network from OpenStreetMap (Haklay & Weber, 2008). For each sampling point, we collected street view images from four degrees (0, 90, 180 and 270), as suggested by previous studies (Wang et al., 2019). In total, we collected more than 0.2 million street view images from 55,715 sampling points.

Previous studies show that streetscape trees and grasses have different influences on residents' well-being since streetscape trees have a stronger effect on mitigating air pollution than grasses (Wang et al., 2019). Therefore, we calculated both SV-trees (SV-tree) and SV-grasses (SV-grass) exposure based on street view images and a machine learning approach. Since street view data was collected within participants' residential neighbourhood, SV can reflect people's daily and visual streetscape greenness exposure (Wang et al., 2020). First, we trained a fully convolutional neural network (FCN-8s; Kang & Wang, 2014) based on an online ADE20K annotated images data set (Zhou et al., 2019) for semantic image segmentation. Second, after the training process, the accuracy of the FCN-8s was 0.825 and capable of identifying trees and grasses at an acceptable level. Following previous studies (Wang et al., 2019), SV-tree and SV-grass per sampling point were determined as the proportion of tree or grass pixels per image to the total number of pixels per image. We calculated the SV-tree and SV-grass for each neighbourhood by averaging the SV-tree and SV-grass scores for all sampling points within 1000-metre circular buffers around the centroid of each targeted neighbourhood.

2.3.2 | Building density

We used the plot ratio (total floor area/net land area) to assess building density in ArcGIS version 10.2. First, residential building density data were collected from city planning documents via the urban data group (*cheng shi shu ju tuan*), a leading data media platform in China (https://www.metrodata.cn/). This data provide information on the number of floors and the total floor area for each building. Second, the net land area for each neighbourhood was calculated. Last, the plot ratio (the total area of all buildings in the targeted neighbourhood/net land area of the targeted neighbourhood) was calculated for each neighbourhood based on the 'spatial join' command in ArcGIS.

2.4 | Covariates

Following previous studies (He et al., 2022; Wang et al., 2020), we also controlled some socioeconomic, demographic and environment covariates. Socioeconomic covariates include homeownership (homeownership vs. non-homeowner), household income (<4999 RMB per month vs. >5000 and <14,999 RMB per month vs. >15,000 RMB per month), educational attainment (high school level and below vs. above high school level), employment status (employed vs. others) and hukou status (local hukou vs. none-local hukou). Demographic covariates include gender (male vs. female), age (<39 years old vs. >39 and <60 years old vs. >60 years old) and marital status (married vs. others). We also included several built environment indicators including distance to the nearest park (km), distance to the nearest tertiary A-level hospital (km), and distance to the nearest subway (km). The information on built environment indicators was also collected in 2013. All of the descriptive statistics are presented in Table 1.

2.5 | Statistical analysis

We used the multilevel logistic regressions (Raudenbush & Bryk, 2002) to examine the associations amongst SV-tree, SV-grass and the likelihood of reporting low SWB. In the models, individuals at Level 1 were nested within neighbourhoods at Level 2. Variance inflation factors (VIF = 1.53) suggested no severe multicollinearity amongst the independent variables. We used moderation analysis to explore the interaction term between SV-tree (SV-grass) exposure and plot ratio. First, we regressed respondents' odds of reporting low SWB on the SV-tree (SV-grass) exposure and plot ratio (Model 1). Second, the interaction term between SV-tree exposure and plot ratio was added to Model 1d (Model 2). Last, the interaction term between SV-grass exposure and plot ratio was added to Model 1d (Model 3). We mainly focused on the direction and significance level of the interaction term. If the direction of the interaction term is the same as streetscape greenness exposure, then it means the effect of streetscape greenness exposure increases with building density. However, if the direction of the interaction term is the opposite of streetscape greenness exposure, the effect of streetscape greenness exposure decreases with building density. Existing literature found that the effect of greenness on well-being may vary due to people's socioeconomic and demographic characteristics such as age, gender and income (Mitchell et al., 2015; Richardson & Mitchell, 2010). Therefore, in the next step, we conducted four exploring heterogeneous effects (Model 4–11) to test whether the relationship between SV-tree (SV-grass) exposure and respondents' odds of reporting low SWB varies by different socioeconomic and demographic characteristics. As for sensitivity analysis (supplement file), we first changed the plot ratio to the building coverage ratio (Model S1). Second, we set SWB as an ordinal variable and repeat the analysis using the multilevel ordered logit model (Model S2). The analyses were performed by Stata 15.1 (StataCorp.) using the ‘melogit’ commands.

3 | RESULTS

Table 2 illustrates the baseline model for the results of SV-tree and SV-grass on respondents' odds of reporting low SWB. Model 1 showed the relationship between SV-tree, SV-grass, plot ratio, and respondents' odds of reporting low SWB. Both SV-tree (OR = 0.826, 95% CI: 0.507–0.939) and SV-grass (OR = 0.854, 95% CI: 0.552–0.993) were negatively associated with respondents' odds of reporting low SWB. However, respondents living in a neighbourhood with Q3 (OR = 1.252, 95% CI: 1.167–2.04) and Q4 (OR = 1.192, 95% CI: 1.016–1.983) plot ratio were more likely to report low SWB than those who live in neighbourhood with Q1 plot ratio. As for

TABLE 1 Descriptive statistics

Variables	Proportion/mean (SD)
Dependent variables	
Subjective well-being (%)	
High	94.391
Low	5.609
Independent variables	
SV-tree median(IQR)	0.126 (0.091)
SV-grass median(IQR)	0.007 (0.007)
Plot ratio (total floor area/net land area)	
First quartile (Q1)	0.364 (0.210)
Second quartile (Q2)	0.874 (0.131)
Third quartile (Q3)	1.238 (0.074)
Fourth quartile (Q4)	1.603 (0.195)
Covariates	
Homeownership (%)	
Homeowner	51.109
Non-homeowner	48.891
Income level (%)	
<4999 RMB per month	27.479
>5000 and <14,999 RMB per month	55.978
>15,000 RMB per month	16.543
Sex (%)	
Male	51.304
Female	48.696
Age (%)	
<39 years old	72.326
>39 and <60 years old	24.696
>60 years old	2.978
Educational attainment level (%)	
High school level and below	36.630
Above high school level	63.370
Hukou status (%)	
Local hukou	64.304
None-local hukou	35.696
Marital status (%)	
Married	61.196
Others	38.804
Employment status (%)	
Employed	90.130
Others	9.870
Distance to amenities (km)	
Distance to park	3.079 (2.376)
Distance to hospital	0.432 (0.388)
Distance to subway	1.671 (1.587)

Abbreviations: IQR, interquartile range; SD, standard deviation; SV, streetscape vegetation.

TABLE 2 Baseline models

	Model 1 OR (95% CI)	Model 2 OR (95% CI)	Model 3 OR (95% CI)
Fixed part			
Independent variables			
SV-tree	0.826 (0.507–0.939)**	0.854 (0.562–0.998)**	0.827 (0.558–0.941)**
SV-grass	0.854 (0.552–0.993)**	0.858 (0.553–0.903)**	0.817 (0.527–0.988)**
Plot ratio (ref. = Q1)			
Q2	1.053 (0.673–1.646)	1.605 (0.675–3.816)	1.180 (0.619–2.252)
Q3	1.252 (1.167–2.045)**	1.128 (1.104–2.930)**	1.356 (1.183–2.693)**
Q4	1.192 (1.016–1.983)**	1.163 (1.103–2.707)**	1.389 (1.113–3.143)**
Interaction term			
SV-tree × plot ratio (Q2)		0.721 (0.403–0.889)**	
SV-tree × plot ratio (Q3)		1.075 (0.613–1.885)	
SV-tree × plot ratio (Q4)		1.146 (1.063–2.087)**	
SV-grass × plot ratio (Q2)			1.911 (0.614–2.350)
SV-grass × plot ratio (Q3)			1.941 (1.442–2.381)**
SV-grass × plot ratio (Q4)			1.877 (1.493–2.561)**
Covariates			
Age (ref: <39 years old)			
>39 and <60 years old	1.064 (0.717–1.579)	1.059 (0.714–1.572)	1.060 (0.714–1.573)
>60 years old	0.645 (0.210–1.984)	0.654 (0.213–2.006)	0.642 (0.209–1.975)
Homeowner (ref: non-homeowner)	0.504 (0.349–0.727)***	0.501 (0.347–0.723)***	0.502 (0.348–0.725)***
Local hukou (ref: non-local hukou)	0.778 (0.552–1.098)	0.788 (0.559–1.112)	0.780 (0.553–1.101)
Income level (ref: <4999 RMB per month)			
>5000 and <14,999 RMB per month	0.703 (0.507–0.974)**	0.701 (0.506–0.971)**	0.702 (0.507–0.973)**
>15,000 RMB per month	0.731 (0.454–1.177)	0.727 (0.451–1.171)	0.732 (0.455–1.179)
Male (ref: female)	1.343 (1.007–1.791)**	1.339 (1.004–1.786)**	1.342 (1.006–1.790)**
Above high school level (ref: high school level and below)	0.915 (0.663–1.264)	0.909 (0.658–1.256)	0.914 (0.662–1.263)
Married (ref. = others)	0.904 (0.650–1.255)	0.906 (0.653–1.259)	0.905 (0.652–1.257)
Employed (ref. = others)	0.765 (0.437–1.340)	0.771 (0.440–1.349)	0.763 (0.436–1.336)
Distance to hospital	0.989 (0.902–1.994)	0.991 (0.904–1.900)	0.988 (0.901–1.989)
Distance to park	1.342 (1.044–2.135)**	1.353 (1.051–2.151)**	1.337 (1.040–2.126)**
Distance to subway	0.731 (0.901–1.110)	1.005 (0.905–1.117)	1.000 (0.901–1.110)
Constant	0.067 (0.027–0.164)***	0.062 (0.023–0.168)***	0.063 (0.025–0.159)***
Radom part			
Var (Neighbourhoods)	1.435***	1.411***	1.424***
Number of individuals	4600	4600	4600
Number of neighbourhoods	2228	2228	2228
Log-likelihood	−953.495	−952.095	−953.324
AIC	1946.991	1950.192	1952.65

Note: Q2 = the 50th percentile; Q3 = the 75th percentile; Q4 = the 100th percentile.

Abbreviations: AIC, Akaike information criterion; CI, confidence interval; OR, odds ratio; SV, streetscape vegetation.

$^{**}p < 0.05$, $^{***}p < 0.01$.

sensitivity analysis (Table S1), despite some differences in magnitude, the SV-SWB and density-SWB associations remained significant and the signs of their coefficients remained the same across all models. As for covariates, homeowners were less likely to report low SWB compared with non-homeowners (OR = 0.504, 95% CI: 0.349–0.727). Compared to respondents with household income of less than 4999 RMB per month, respondents with household income between 5000–14,999 RMB per month were less likely to report low SWB (OR = 0.703, 95% CI: 0.507–0.974). Last, respondents' odds of reporting low SWB were positively associated with distance to the park (OR = 1.342, 95% CI: 1.044–2.135).

Model 2 showed the moderated effect of the plot ratio in the relationship between SV-tree and respondents' odds of reporting low SWB. There was evidence to suggest that the plot ratio modified the association between SV-tree and respondents' odds of reporting low SWB. For example, compared with living in neighbourhood with Q1 plot ratio, the effect of SV-tree on respondents' odds of reporting low SWB was strengthened in neighbourhood with Q2 plot ratio (OR = 0.721, 95% CI: 0.403–0.889), but was weakened in neighbourhood with Q4 plot ratio (OR = 1.146, 95% CI: 1.063–2.087). Model 3 showed the moderated effect of the plot ratio in the relationship between SV-grass and respondents' odds of reporting low SWB. There was also evidence to suggest that the plot ratio modified the association between SV-grass and respondents' odds of reporting low SWB. For instance, compared with living in neighbourhood with Q1 plot ratio, the effect of SV-grass on respondents' odds of reporting low SWB was weakened in neighbourhood with Q3 plot ratio (OR = 1.941, 95% CI: 1.442–2.381) and Q4 plot ratio (OR = 1.146, 95% CI: 1.493–2.561).

We further examined the association amongst SV-tree, SV-grass, plot ratio and respondents' odds of reporting low SWB with the heterogeneous effects by individual demographic (gender and age) and socioeconomic (income and educational attainment) characteristics. Table 3 showed the heterogeneous effects between male and female groups. Model 4a indicated that SV-tree (OR = 0.735, 95% CI: 0.418–0.893) and SV-grass (OR = 0.860, 95% CI: 0.479–0.914) were negatively associated with male respondents' odds of reporting low SWB. Male respondents living in neighbourhood with Q3 (OR = 2.457, 95% CI: 1.704–8.580) and Q4 (OR = 1.467, 95% CI: 1.115–1.901) plot ratio were more likely to report low SWB than those who live in neighbourhood with Q1 plot ratio. The moderation term indicated that compared with living in neighbourhood with Q1 plot ratio, the effect of SV-tree on male respondents' odds of reporting low SWB was strengthened in neighbourhood with Q3 plot ratio (OR = 0.710, 95% CI: 0.326–0.846) but weakened in neighbourhood with Q4 plot ratio (OR = 1.880, 95% CI: 1.545–4.180). However, Model 5a indicated that no evidence can support that SV-tree (OR = 0.998, 95% CI: 0.633–1.905) and SV-grass (OR = 0.866, 95% CI: 0.570–1.433) were negatively associated with female respondents' odds of reporting low SWB. Similar to males, female respondents living in neighbourhood with Q3 (OR = 1.297, 95% CI: 1.186–2.610) and Q4 (OR = 1.843, 95% CI: 1.463–7.334) plot ratio were more likely to report low SWB than those who live in neighbourhood with Q1 plot ratio. The moderation term indicated that compared with living in neighbourhood with Q1 plot ratio, the effect of SV-tree on female respondents' odds of reporting low SWB was strengthened in neighbourhood with Q3 plot ratio (OR = 0.700, 95% CI: 0.314–0.958) but weakened in neighbourhood with Q4 plot ratio (OR = 1.013, 95% CI: 1.080–1.597).

TABLE 3 Heterogeneous effects by gender

	Males		Females	
	Model 4a	Model 4b	Model 5a	Model 5b
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
Independent variables				
SV-tree	0.735 (0.418–0.893)**	0.727 (0.531–0.995)**	0.998 (0.633–1.905)	0.914 (0.753–1.364)
SV-grass	0.860 (0.479–0.914)**	0.792 (0.418–0.905)**	0.866 (0.570–1.433)	0.916 (0.837–1.769)
Plot ratio (ref. = Q1)				
Q2	2.028 (0.660–6.232)	1.384 (0.606–3.160)	1.285 (0.365–4.526)	0.992 (0.381–2.585)
Q3	2.457 (1.704–8.580)**	1.662 (1.272–4.114)**	1.297 (1.186–2.610)**	1.232 (1.086–3.124)**
Q4	1.467 (1.115–1.901)**	1.673 (1.279–4.837)**	1.843 (1.463–7.334)**	1.169 (1.072–3.670)**
Interaction term				
SV-tree × plot ratio (Q2)	0.710 (0.326–0.846)**		0.700 (0.314–0.958)**	
SV-tree × plot ratio (Q3)	1.665 (0.300–2.474)		1.378 (0.671–2.830)	
SV-tree × plot ratio (Q4)	1.880 (1.545–4.180)**		1.013 (1.080–1.597)**	
SV-grass × plot ratio (Q2)		1.978 (0.592–2.616)		1.819 (0.452–1.484)
SV-grass × plot ratio (Q3)		1.841 (1.499–2.416)**		1.998 (0.995–2.676)**
SV-grass × plot ratio (Q4)		1.829 (1.395–2.740)**		1.925 (1.406–2.107)**
Log-likelihood	−522.861	−526.384	−417.179	−418.982
AIC	1089.724	1096.768	876.358	879.964

Note: Models were fully adjusted. Q2 = the 50th percentile; Q3 = the 75th percentile; Q4 = the 100th percentile.

Abbreviations: AIC, Akaike information criterion; CI, confidence interval; OR, odds ratio; SV, streetscape vegetation.

** $p < 0.05$.

The moderation term in Model 4b suggested that compared with living in neighbourhood with Q1 plot ratio, the effect of SV-grass on male respondents' odds of reporting low SWB was weakened in neighbourhood with Q3 plot ratio (OR = 1.841, 95% CI: 1.499–2.416) and Q4 plot ratio (OR = 1.829, 95% CI: 1.395–2.740). Hence, the moderation term in Model 5b suggested that compared with living in neighbourhood with Q1 plot ratio, the effect of SV-grass on female respondents' odds of reporting low SWB was weakened in neighbourhood with Q3 plot ratio (OR = 1.998, 95% CI: 0.995–2.676) and Q4 plot ratio (OR = 1.925, 95% CI: 1.406–2.107).

Table 4 showed the heterogeneous effects of age. Model 6a indicated that SV-tree (OR = 0.741, 95% CI:0.455–0.906) and SV-grass (OR = 0.770, 95% CI: 0.417–0.881) were negatively associated with young adults' odds of reporting low SWB. Young adults living in neighbourhood with Q3 (OR = 1.855, 95% CI: 1.279–2.619) and Q4 (OR = 1.560, 95% CI: 1.164–1.911) plot ratio were more likely to report low SWB than those who live in neighbourhood with Q1 plot ratio. The moderation term indicated that compared with in neighbourhood with Q1 plot ratio, the effect of SV-tree on young adults' odds of reporting low SWB was strengthened in neighbourhood with Q3 plot ratio (OR = 0.792, 95% CI: 0.524–0.880) but weakened in neighbourhood with Q4 plot ratio (OR = 1.428, 95% CI: 1.200–2.913). However, Model 7a indicated that no evidence can support that SV-tree (OR = 0.876, 95% CI:0.621–3.508) and SV-grass (OR = 0.965, 95% CI:0.641–1.452) were negatively associated with middle-age and older adults' odds of reporting low SWB. Similar to young adults, middle-aged and older adults living in neighbourhood with Q3 (OR = 1.065, 95% CI: 1.009–1.563) and Q4 (OR = 1.865, 95% CI: 1.535–2.807) plot ratio were more likely to report low SWB than those who live in neighbourhood with Q1 plot ratio. The moderation term indicated that compared with living in neighbourhood with Q1 plot ratio, the effect of SV-tree on middle-age and older adults' odds of reporting low SWB was strengthened in the neighbourhood with a Q3 plot ratio (OR = 0.050, 95% CI: 0.006–0.404).

The moderation term in Model 6b suggested that compared with living in neighbourhood with Q1 plot ratio, the effect of SV-grass on young adults' odds of reporting low SWB was weakened in neighbourhood with Q3 plot ratio (OR = 1.153, 95% CI: 1.108–1.493) and Q4 plot ratio (OR = 1.138, 95% CI: 1.074–2.258). Hence, the moderation term in Model 7b suggested that compared with living in neighbourhood with Q1 plot ratio, the effect of SV-grass on middle-age and older adults' odds of reporting low SWB was weakened in neighbourhood with Q3 plot ratio (OR = 2.789, 95% CI: 2.358–3.741).

Table 5 showed the heterogeneous effects of educational attainment. Model 8a indicated that SV-tree (OR = 0.876, 95% CI:0.406–0.890) and SV-grass (OR = 0.803, 95% CI: 0.436–0.900) were negatively associated with odds of reporting low SWB for respondents with high school and below education attainment. Respondents with high school and below education attainment living in neighbourhood with Q3 (OR = 1.816, 95% CI: 1.155–4.288) and Q4 (OR = 1.582, 95% CI: 1.090–3.754) plot ratio were more likely to report low SWB than those who live in neighbourhood with Q1 plot ratio. The moderation

TABLE 4 Heterogeneous effects by age

	Young adults		Middle-age and older adults	
	Model 6a	Model 6b	Model 7a	Model 7b
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
Independent variables				
SV-tree	0.741 (0.455–0.906)**	0.831 (0.636–0.886)**	0.876 (0.621–3.508)	0.780 (0.491–1.238)
SV-grass	0.770 (0.417–0.881)**	0.850 (0.510–0.904)**	0.965 (0.641–1.452)	0.735 (0.425–2.497)
Plot ratio (ref. = Q1)				
Q2	1.063 (0.405–2.791)	1.026 (0.499–2.110)	1.740 (0.559–2.750)	1.184 (0.709–2.701)
Q3	1.855 (1.279–2.619)**	1.123 (1.110–2.476)**	1.065 (1.009–1.563)**	1.646 (1.201–1.974)**
Q4	1.560 (1.164–1.911)**	1.829 (1.315–2.185)**	1.865 (1.535–2.807)**	1.135 (1.057–1.731)**
Interaction term				
SV-tree × plot ratio (Q2)	0.792 (0.524–0.880)**		0.050 (0.006–0.404)**	
SV-tree × plot ratio (Q3)	1.178 (0.601–2.308)		1.064 (0.223–1.838)	
SV-tree × plot ratio (Q4)	1.428 (1.200–2.913)**		1.136 (0.204–1.982)	
SV-grass × plot ratio (Q2)		1.017 (0.659–1.570)		2.262 (0.060–3.145)
SV-grass × plot ratio (Q3)		1.153 (1.108–1.493)**		2.789 (2.358–3.741)**
SV-grass × plot ratio (Q4)		1.138 (1.074–2.258)**		2.428 (0.134–3.368)
Log-likelihood	−711.863	−712.401	−223.787	−227.002
AIC	1465.726	1466.804	491.575	498.005

Note: Models were fully adjusted. Q2 = the 50th percentile; Q3 = the 75th percentile; Q4 = the 100th percentile.
Abbreviations: AIC, Akaike information criterion; CI, confidence interval; OR, odds ratio; SV, streetscape vegetation.
**$p < 0.05$.

term indicated that compared with living in neighbourhood with Q1 plot ratio, the effect of SV-tree on odds of reporting low SWB for respondents with high school and below education attainment was strengthened in neighbourhood with Q3 plot ratio (OR = 0.542, 95% CI: 0.191–0.837) but weakened in neighbourhood with Q4 plot ratio (OR = 1.928, 95% CI: 1.666–5.586). Also, Model 9a indicated that SV-tree (OR = 0.840, 95% CI:0.513–0.975) and SV-grass (OR = 0.886, 95% CI:0.446–0.98) were negatively associated with odds of reporting low SWB for respondents with above high school education attainment. Respondents with above high school education attainment living in neighbourhood with Q3 (OR = 1.056, 95% CI: 1.004–4.887) and Q4 (OR = 1.139, 95% CI: 1.032–3.908) plot ratio were more likely to report low SWB than those who live in neighbourhood with Q1 plot ratio. The moderation term indicated that compared with living in neighbourhood with Q1 plot ratio, the effect of SV-tree on the odds of reporting low SWB for respondents with above high school education attainment was weakened in neighbourhood with Q4 plot ratio (OR = 1.059, 95% CI: 1.003–1.485).

The moderation term in Model 8b suggested that compared with living in neighbourhood with Q1 plot ratio, the effect of SV-grass on odds of reporting low SWB for respondents with high school and below education attainment was weakened in neighbourhood with Q3 plot ratio (OR = 1.312, 95% CI: 1.105–2.444) and Q4 plot ratio (OR = 1.832, 95% CI: 1.320–2.168). Hence, the moderation term in Model 9b suggested that compared with living in neighbourhood with Q1 plot ratio, the effect of SV-grass on odds of reporting low SWB for respondents with above high school education attainment was weakened in neighbourhood with Q4 plot ratio (OR = 1.976, 95% CI: 1.426–2.799).

Table 6 showed the heterogeneous effects of income. Model 10a indicated that SV-tree (OR = 0.915, 95% CI:0.787–0.945) and SV-grass (OR = 0.879, 95% CI: 0.823–0.916) were negatively associated with odds of reporting low SWB for respondents with low income. Respondents with low income living in neighbourhood with Q3 (OR = 2.259, 95% CI: 1.798–3.313) and Q4 (OR = 1.395, 95% CI: 1.272–3.154) plot ratio were more likely to report low SWB than those who live in neighbourhood with Q1 plot ratio. The moderation term indicated that compared with in neighbourhood with Q1 plot ratio, the effect of SV-tree on odds of reporting low SWB for respondents with low income was strengthened in neighbourhood with Q3 plot ratio (OR = 0.462 95% CI: 0.190–0.821) but weakened in neighbourhood with Q4 plot ratio (OR = 1.772, 95% CI: 1.316–1.891). However, Model 11a indicated that no evidence can support that SV-tree (OR = 0.595, 95% CI:0.321–1.103) and SV-grass (OR = 0.679, 95% CI:0.586–1.752) were also negatively associated with odds of reporting low SWB for respondents with middle and high income. Respondents with middle- and high-income living in neighbourhood with Q4 (OR = 1.105, 95% CI: 1.007–3.133) plot ratio were more likely to report low SWB than those who live in neighbourhood with Q1 plot ratio. No evidence can support that the plot ratio moderates the association between SV-tree and the odds of reporting low SWB for respondents with middle and high income.

TABLE 5 Heterogeneous effects by education level

	High school level and below		Above high school level	
	Model 8a	Model 8b	Model 9a	Model 9b
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
Independent variables				
SV-tree	0.876 (0.406–0.890)**	0.991 (0.695–0.999)**	0.840 (0.513–0.975)**	0.746 (0.556–0.902)**
SV-grass	0.803 (0.436–0.900)**	0.830 (0.583–0.902)**	0.886 (0.446–0.988)**	0.811 (0.575–0.893)**
Plot ratio (ref. = Q1)				
Q2	1.490 (0.526–3.798)	1.175 (0.397–3.477)	1.654 (0.473–3.876)	1.231 (0.551–2.749)
Q3	1.816 (1.155–4.288)**	1.392 (1.164–4.177)**	1.056 (1.004–4.887)**	1.274 (1.106–3.587)**
Q4	1.582 (1.090–3.754)**	1.870 (1.476–3.339)**	1.139 (1.032–3.908)**	1.314 (1.179–3.604)**
Interaction term				
SV-tree × plot ratio (Q2)	0.542 (0.191–0.837)**		0.797 (0.394–1.612)	
SV-tree × plot ratio (Q3)	1.862 (0.687–5.044)		1.055 (0.365–1.561)	
SV-tree × plot ratio (Q4)	1.928 (1.666–5.586)**		1.059 (1.003–1.485)**	
SV-grass × plot ratio (Q2)		1.143 (0.493–1.803)		1.959 (0.523–2.412)
SV-grass × plot ratio (Q3)		1.312 (1.105–2.444)**		1.9712 (0.418–2.213)
SV-grass × plot ratio (Q4)		1.832 (1.320–2.168)**		1.976 (1.426–2.799)**
Log-likelihood	−383.346	−387.057	−553.714	−553.296
AIC	810.6931	818.115	1149.429	1148.593

Note: Models were fully adjusted. Q2 = the 50th percentile; Q3 = the 75th percentile; Q4 = the 100th percentile.
Abbreviations: AIC, Akaike information criterion; CI, confidence interval; OR, odds ratio; SV, streetscape vegetation.
** $p < 0.05$.

TABLE 6 Heterogeneous effects by income level

	Low income		Middle and high income	
	Model 10a	Model 10b	Model 11a	Model 11b
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
Independent variables				
SV-tree	0.915 (0.787–0.945)**	0.958 (0.672–0.995)**	0.595 (0.321–1.103)*	0.756 (0.556–1.028)*
SV-grass	0.879 (0.823–0.916)***	0.810 (0.747–0.948)**	0.679(0.586–1.752)	0.879(0.467–2.051)
Plot ratio (ref. = Q1)				
Q2	2.606(0.639–4.631)	1.875(0.313–2.442)	1.173(0.377–3.647)	1.172(0.634–3.420)
Q3	2.259 (1.798–3.313)**	1.444 (1.119–4.020)**	1.022(0.140–1.942)	1.266(0.499–3.212)
Q4	1.395 (1.272–3.154)**	1.065 (1.001–3.921)*	1.105 (1.007–3.133)**	1.621 (1.557–4.713)**
Interaction term				
SV-tree × plot ratio (Q2)	0.462 (0.190–0.821)**		1.292(0.444–2.219)	
SV-tree × plot ratio (Q3)	1.0577(0.263–2.268)		1.230(0.772–3.875)	
SV-tree × plot ratio (Q4)	1.772 (1.316–1.891)**		1.006(0.646–3.422)	
SV-grass × plot ratio (Q2)		1.503(0.534–1.884)		1.915(0.488–2.361)
SV-grass × plot ratio (Q3)		1.957 (1.550–2.667)**		1.917(0.532–2.581)
SV-grass × plot ratio (Q4)		1.878 (1.345–2.236)**		1.970(0.410–2.846)
Log-likelihood	−333.755	−335.492	−611.126	−612.285
AIC	709.511	712.984	1266.252	1268.57

Note: Models were fully adjusted. Q2 = the 50th percentile; Q3 = the 75th percentile; Q4 = the 100th percentile.
Abbreviations: AIC, Akaike information criterion; CI, confidence interval; OR, odds ratio; SV, streetscape vegetation.
**p* < 0.10.; ***p* < 0.05.; ****p* < 0.01.

The moderation term in Model 10b suggested that compared with in neighbourhood with Q1 plot ratio, the effect of SV-grass on odds of reporting low SWB for respondents with low income was weakened in neighbourhood with Q3 plot ratio (OR = 1.957, 95% CI: 1.550–2.667) and Q4 plot ratio (OR = 1.878, 95% CI: 1.345–2.236). Hence, the moderation term in Model 11b suggested that no evidence can support that the plot ratio moderates the association between SV-grass and the odds of reporting low SWB for respondents with middle and high income.

4 | DISCUSSION

4.1 | Key findings

This study finds that both streetscape trees and grass are positively associated with SWB whilst building density is negatively associated with SWB. Our findings suggest that building density moderates the association between SV and SWB. Relatively lower-middle building density strengthens the positive effect of streetscape trees on SWB, whilst high building density weakens the positive effect of streetscape trees on SWB. Hence, higher-middle and high building density weaken the positive effect of streetscape grasses on SWB. Last, the effect of street streetscape trees, grasses and building density on SWB is varied significantly by individual demographic and socioeconomic characteristics such as sex, age, educational attainment and income.

4.2 | Independent effect of street trees, grass and building density on SWB

Our results suggest that residential street trees may exert beneficial effects on SWB in an urban population. Previous studies in Australia (Astell-Burt & Feng, 2019), New York City in America (Reid et al., 2017) and Guangzhou (China; Wang et al., 2019) also found that neighbourhood tree canopy was positively related to health outcomes. First, street trees can reduce people's stress and help them recover from pressure (Jiang et al., 2014, 2016). Second, street trees not only benefit people's mental well-being by decreasing objective pollution harms (i.e. nitrogen dioxide and particles smaller than 10 or 2.5 microns) but also benefit people's mental well-being through the reduction of people's subjective perceived pollution (Wang et al., 2019). Last, shade provision of street trees can encourage people to take more outdoor physical activity (e.g. walking) which benefits well-being (Li et al., 2018; Wang et al., 2019, 2020). Hence, street trees also offer people an open space for contacting others, which enhances their cohesion (Wang et al., 2019). Our results also suggest streetscape grass is positively associated with SWB. This is different from findings from previous studies in Australia (Astell-Burt & Feng, 2019) and America (Reid et al., 2017), but consistent with previous evidence in China (Wang et al., 2019). Reid et al. (2017) pointed out that grasses affect health in a different way with trees, which may explain its insignificant association with health. Astell-Burt and Feng (2019) suggested that trees are more beneficial for mental well-being since it is more supportive of biodiversity than grasses. However, a recent study in China found that street grasses also benefit people's mental well-being by decreasing objective pollution harms (i.e. nitrogen dioxide) and people's perceived pollution (Wang et al., 2019). Another reason for the inconsistency of the grass-health association may be because of the difference in the definition of street grasses (Wood et al., 2018). The quality of street grasses is also relevant to impose psychological restorative benefits. This study indicates that building density is negatively associated with SWB in an urban population. However, previous studies in Hong Kong found that building density was positively related to health by improving acoustic comforts (Chan & Liu, 2018). We only found a significant association between building density and SWB when the density is high enough (Q3 and Q4). It means that when building density increases within the appropriate limits, it may benefit residents' SWB, but if the density is too high it may exert adverse effects on SWB.

4.3 | Joint effect of street trees, grass and building density on SWB

Our findings suggest that building density moderates the association between SV and SWB. Relatively lower-middle (Q2) building density strengthens the positive effect of streetscape trees on SWB, whilst high (Q4) building density weakens the positive effect of streetscape trees on SWB. This phenomenon can be explained by the following reasons: (1) With the slight increase in building density (Q2), the density of street tree cover may also increase. This further makes residents share a more compact open space and increases social contacts which may facilitate neighbourhood social cohesion and encourage residents to take outdoor group sports (Talen & Koschinsky, 2014). However, when building density gets too high (Q4), the cover of the tree canopy may be too low to support a comfortable open space; (2) When street trees get denser, they are more likely to block different kinds of pollutants (Huang et al., 2019), but if the cover of the tree canopy gets too low, it can not mitigate environmental stressors such as air pollution (Huang et al., 2019); (3) Previous studies have proven that the restorative effect of trees on stress recovery increases with a slight increase of its density, but if the density of trees gets too high, its restorative effect decreases (Jiang et al., 2014). However, no evidence can support that the slight increase in building density may also strengthen the effect of streetscape grasses. We found that higher-middle (Q3) and high (Q4) building density weakens the positive effect of streetscape grasses on SWB. First, the cover of street grassland may become too low and dense with the increase in building density and may not support outdoor physical activity and social contact (Peters et al., 2010). Hence, a dense street grassland may cause conflict in the neighbourhood, since residents will compete for limited open space resources (Burton et al., 1996). Second, when street grasses get too dense, its mitigation effect on environmental stressors also decreases (Vieira et al., 2018). Third, a dense street grassland can not offer a comfortable place for various species which may reduce its biodiversity and psychological restorative benefits (Wood et al., 2018).

Our stratified and moderation analysis suggests that the association amongst street vegetation, building density and SWB tends to vary with individual socio-demographic factors. We found that males can benefit more from street vegetation than females which is consistent with previous studies (Richardson & Mitchell, 2010), This may be due to the reason that males spend more time on the street for different outdoor activities than females (Jiang et al., 2014). Street vegetation is more beneficial for young adults than for older adults. This can be explained by the reason that young adults are more likely to spend their leisure time in physical activities (i.e. walking and cycling) on the street than older adults since they are less likely to be functionally restricted (Sang et al., 2016). We also found that people with low-income benefit more from street vegetation than people with high incomes. People with high income can pay for better health-related services, but people with low income have to rely on public resources such as public green infrastructures on the street (Liu et al., 2017; Mitchell et al., 2015; Pan et al., 2021; Salehi et al., 2017).

4.4 | Policy implication and limitations

Since both streetscape trees and grass are positively associated with SWB, policy makers should improve the provision of street vegetation to promote residents' well-being. Second, the plot ratio is negatively associated with SWB, so laws and regulations regulating the building density should be perfected. Third, the effects of greenspace streetscape trees and grass may be modified by building density, so street vegetation should be planned based on the local neighbourhood building density. Last, we found that the effect of SV is more beneficial for disadvantaged groups (e.g. low income groups), so more SV should be planned for deprived neighbourhoods, which may be useful narrow health inequalities and improve social justice.

Our study has several limitations due to data constraints. First, our cross-sectional study design makes it difficult to infer causation between streetscape greenness exposure and SWB. Second, the duration of exposure to streetscape greenness was not taken into account and other detailed information on streetscape greenness is still unknown. This may lead to the Uncertain Geographic Context Problem regarding the influences of streetscape greenness (Kwan, 2012). Third, street view data can not identify dynamic seasonal effects of changes in streetscape greenness. Hence, inconsistent collected time of survey and street view data, and errors in identification of the vegetation in the images may lead to some bias.

5 | CONCLUSION

This study systematically investigates the role of building density in the association between street vegetation and SWB amongst people living in Chinese cities. Results from statistical analyses show that both streetscape trees and grass are positively associated with SWB whilst building density is negatively associated with SWB. The moderation analysis indicates that the effects of greenspace streetscape trees and grass may be modified by building density. Hence, the decomposition analysis provides the insight that the effect of street vegetation and building density on SWB is varied significantly by individual demographic and socioeconomic characteristics such as sex, age and income. The above findings highlight the importance of considering the context effect of density for urban greenness research. To create healthy cities through urban planning and design, policymakers should focus on the perceived benefits of street vegetation and building density at the neighbourhood scale.

AUTHOR CONTRIBUTIONS

Ruoyu Wang and Wenjie Wu conceptualised and designed the current study. Ruoyu Wang, Linchuan Yang and Yao Yao conducted the analyses. Wenjie Wu provided supervision to Ruoyu Wang. Ruoyu Wang developed the original draft and all authors reviewed and edited subsequent drafts.

ACKNOWLEDGEMENTS

This work was supported by the National Natural Science Foundation of China (41971194 and 41801306), the National Office for Philosophy and Social Sciences (20ZDA037), the Fundamental Research Funds for the Central Universities (21621105), and the Outstanding Innovative Talents Cultivation Funded Programs for Doctoral Students of Jinan University (2021CXB013) and Open Fund of State Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University (Grant No.18S01). We also thank the Research Center for the Industrial Development of Guangdong and its Regional Cooperation with Hongkong, Macau and Taiwan, and the Research Center on Economic Development in Guangdong-Hongkong-Macau Greater Bay Area for funding support.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

REFERENCES

Agresti, A. (2003). *Categorical data analysis*. John Wiley & Sons.

Astell-Burt, T., & Feng, X. (2019). Association of urban green space with mental health and general health among adults in Australia. *JAMA Network Open*, *2*, e198209.

Azad, S. P., Morinaga, R., & Kobayashi, H. (2018). Effect of housing layout and open space morphology on residential environments–applying new density indices for evaluation of residential areas case study: Tehran, Iran. *Journal of Asian Architecture and Building Engineering*, *17*, 79–86.

Burton, E., Williams, K., & Jenks, M. (1996). The compact city and urban sustainability: Conflicts and complexities. In M. Jenks, E. Burton, & K. Williams (Eds.), *The compact city—a sustainable urban form?* (pp. 231–247). E & FN Spon.

Campbell, A., Converse, P. E., & Rodgers, W. L. (1976). *The quality of American life: Perceptions, evaluations, and satisfactions*. Russell Sage Foundation.

Chan, I. Y., & Liu, A. M. (2018). Effects of neighborhood building density, height, greenspace, and cleanliness on indoor environment and health of building occupants. *Building and Environment*, *145*, 213–222.

Guedes, I. C. M., Bertoli, S. R., & Zannin, P. H. (2011). Influence of urban shapes on environmental noise: A case study in Aracaju—Brazil. *Science of the Total Environment*, *412*, 66–76.

Guo, Y., Fu, Y., & Xu, Y. (2021). Satisfaction with neighbourhood environment moderates the associations between objective neighbourhood environment and leisure-time physical activity in older adults in Beijing, China. *Health & Social Care in the Community*, *29*(1), 206–214.

Haklay, M., & Weber, P. (2008). Openstreetmap: User-generated street maps. *IEEE Pervasive Computing*, *7*, 12–18.

He, D., Miao, J., Lu, Y., Song, Y., Chen, L., & Liu, Y. (2022). Urban greenery mitigates the negative effect of urban density on older adults' life satisfaction: Evidence from Shanghai, China. *Cities*, *124*, 103607.

Ho, D. C.-W., Chau, K.-W., Cheung, A. K.-C., Yau, Y., Wong, S.-K., Leung, H.-F., Lau, S. S.-Y., & Wong, W.-S. (2008). A survey of the health and safety conditions of apartment buildings in Hong Kong. *Building and Environment*, *43*, 764–775.

Huang, Y.-D., Li, M.-Z., Ren, S.-Q., Wang, M.-J., & Cui, P.-Y. (2019). Impacts of tree-planting pattern and trunk height on the airflow and pollutant dispersion inside a street canyon. *Building and Environment*, *165*, 106385.

Jang, H. S., Lee, S. C., Jeon, J. Y., & Kang, J. (2015). Evaluation of road traffic noise abatement by vegetation treatment in a 1:10 urban scale model. *The Journal of the Acoustical Society of America*, *138*, 3884–3895.

Jiang, B., Chang, C.-Y., & Sullivan, W. C. (2014). A dose of nature: Tree cover, stress reduction, and gender differences. *Landscape Urban Plan*, *132*, 26–36.

Jiang, B., Li, D., Larsen, L., & Sullivan, W. C. (2016). A dose-response curve describing the relationship between urban tree cover density and self-reported stress recovery. *Environment and Behavior*, *48*, 607–629.

Jiang, Y., Huang, G., & Fisher, B. (2019). Air quality, human behavior and urban park visit: A case study in Beijing. *Journal of Cleaner Production*, *240*, 118000.

Kang, K., & Wang, X. (2014). Fully convolutional neural networks for crowd segmentation. *Computer Science*, *49*, 25–30.

Kaplan, R. (2001). The nature of the view from home: Psychological benefits. *Environment and Behavior*, *33*, 507–542.

Kwan, M.-P. (2012). The uncertain geographic context problem. *Annals of the Association of American Geographers*, *102*, 958–968.

Li, X., Ratti, C., & Seiferling, I. (2018). Quantifying the shade provision of street trees in urban landscape: A case study in Boston, USA, using Google street view. *Landscape Urban Plan*, *169*, 81–91.

Li, X., Zhang, C., Li, W., & Kuzovkina, Y. A. (2016). Environmental inequities in terms of different types of urban greenery in Hartford, Connecticut. *Urban Forestry & Urban Greening*, *18*, 163–172.

Liu, H., Li, F., Xu, L., & Han, B. (2017). The impact of socio-demographic, environmental, and individual factors on urban park visitation in Beijing, China. *Journal of Cleaner Production*, *163*, S181–S188.

Liu, Y., Wang, R., Lu, Y., Li, Z., Chen, H., Cao, M., Zhang, Y., & Song, Y. (2020). Natural outdoor environment, neighbourhood social cohesion and mental health: Using multilevel structural equation modelling, streetscape and remote-sensing metrics. *Urban Forestry & Urban Greening*, *48*, 126576.

Liu, Y., Zhang, Y., Jin, S. T., & Liu, Y. (2020). Spatial pattern of leisure activities among residents in Beijing, China: Exploring the impacts of urban environment. *Sustainable Cities and Society*, *52*, 101806.

Liu, Z., Yang, A., Gao, M., Jiang, H., Kang, Y., Zhang, F., & Fei, T. (2019). Towards feasibility of photovoltaic road for urban traffic-solar energy estimation using street view image. *Journal of Cleaner Production*, *228*, 303–318.

Mao, S., Lu, N., & Xiao, C. (2021). *Perceived neighborhood environment and depressive symptoms among older adults living in urban China: The mediator role of social capital*. Health & Social Care in the Community.

Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A. M., De Vries, S., Triguero-Mas, M., Brauer, M., & Nieuwenhuijsen, M. J. (2017). Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research*, *158*, 301–317.

Mirzaei, P. A., Haghighat, F., Nakhaie, A. A., Yagouti, A., Giguère, M., Keusseyan, R., & Coman, A. (2012). Indoor thermal condition in urban heat Island–development of a predictive tool. *Building and Environment*, *57*, 7–17.

Mitchell, R. J., Richardson, E. A., Shortt, N. K., & Pearce, J. R. (2015). Neighborhood environments and socioeconomic inequalities in mental well-being. *American Journal of Preventive Medicine*, *49*, 80–84.

Niachou, K., Hassid, S., Santamouris, M., & Livada, I. (2008). Experimental performance investigation of natural, mechanical and hybrid ventilation in urban environment. *Building and Environment*, *43*, 1373–1382.

Nieuwenhuijsen, M. J., Khreis, H., Triguero-Mas, M., Gascon, M., & Dadvand, P. (2017). Fifty shades of green: Pathway to healthy urban living. *Epidemiology*, *28*, 63–71.

Pan, H., Liu, Y., & Chen, Y. (2021). The health effect of perceived built environment on depression of elderly people in rural China: Moderation by income. *Health & Social Care in the Community*, *29*(1), 185–193.

Perini, K., & Magliocco, A. (2014). Effects of vegetation, urban density, building height, and atmospheric conditions on local temperatures and thermal comfort. *Urban Forestry & Urban Greening*, *13*, 495–506.

Peters, K., Elands, B., & Buijs, A. (2010). Social interactions in urban parks: Stimulating social cohesion? *Urban Forestry & Urban Greening*, *9*, 93–100.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (Vol. 1). Sage.

Reid, C. E., Clougherty, J. E., Shmool, J. L., & Kubzansky, L. D. (2017). Is all urban green space the same? A comparison of the health benefits of trees and grass in new York City. *International Journal of Environmental Research and Public Health*, *14*, 1411.

Richardson, E. A., & Mitchell, R. (2010). Gender differences in relationships between urban green space and health in the United Kingdom. *Social Science & Medicine*, *71*, 568–575.

Saarloos, D., Alfonso, H., Giles-Corti, B., Middleton, N., & Almeida, O. P. (2011). The built environment and depression in later life: The health in men study. *American Journal of Geriatric Psychiatry*, *19*, 461–470.

Salehi, A., Harris, N., Sebar, B., & Coyne, E. (2017). The relationship between living environment, well-being and lifestyle behaviours in young women in S hiraz, I ran. *Health & Social Care in the Community*, *25*(1), 275–284.

Sang, Å. O., Knez, I., Gunnarsson, B., & Hedblom, M. (2016). The effects of naturalness, gender, and age on how urban green space is perceived and used. *Urban Forestry & Urban Greening*, *18*, 268–276.

Sarkar, C., Webster, C., & Gallacher, J. (2018). Residential greenness and prevalence of major depressive disorders: A cross-sectional, observational, associational study of 94 879 adult UK biobank participants. *The Lancet Planetary Health*, *2*, e162–e173.

Son, J.-Y., Lane, K. J., Lee, J.-T., & Bell, M. L. (2016). Urban vegetation and heat-related mortality in Seoul, Korea. *Environmental Research*, *151*, 728–733.

Song, Y., Chen, B., & Kwan, M.-P. (2020). How does urban expansion impact people's exposure to green environments? A comparative study of 290 Chinese cities. *Journal of Cleaner Production*, *246*, 119018.

Sugiyama, T., Leslie, E., Giles-Corti, B., & Owen, N. (2008). Associations of neighbourhood greenness with physical and mental health: Do walking, social coherence and local social interaction explain the relationships? *Journal of Epidemiology & Community Health*, *62*, e9.

Talen, E., & Koschinsky, J. (2014). The neighborhood quality of subsidized housing. *Journal of the American Planning Association*, *80*, 67–82.

Theodoridis, G., & Moussiopoulos, N. (2000). *Influence of building density and roof shape on the wind and dispersion characteristics in an urban area: A numerical study, urban air quality: Measurement, modelling and management*. Springer.

Ugolini, F., Massetti, L., Pearlmutter, D., & Sanesi, G. (2021). Usage of urban green space and related feelings of deprivation during the COVID-19 lockdown: Lessons learned from an Italian case study. *Land Use Policy*, *105*, 105437.

Vieira, J., Matos, P., Mexia, T., Silva, P., Lopes, N., Freitas, C., Correia, O., Santos-Reis, M., Branquinho, C., & Pinho, P. (2018). Green spaces are not all the same for the provision of air purification and climate regulation services: The case of urban parks. *Environmental Research*, *160*, 306–313.

Wang, Q., & Lan, Z. (2019). Park green spaces, public health and social inequalities: Understanding the interrelationships for policy implications. *Land Use Policy*, *83*, 66–74.

Wang, R., Feng, Z., Pearce, J., Yao, Y., Li, X., & Liu, Y. (2021). The distribution of greenspace quantity and quality and their association with neighbourhood socioeconomic conditions in Guangzhou, China: A new approach using deep learning method and street view images. *Sustainable Cities and Society*, *66*, 102664.

Wang, R., Lu, Y., Wu, X., Liu, Y., & Yao, Y. (2020). Relationship between eye-level greenness and cycling frequency around metro stations in Shenzhen, China: A big data approach. *Sustainable Cities and Society*, *59*, 102201.

Wang, R., Yang, B., Yao, Y., Bloom, M. S., Feng, Z., Yuan, Y., Zhang, J., Liu, P., Wu, W., Lu, Y., Baranyi, G., Wu, R., Liu, Y., & Dong, G. (2019). Residential greenness, air pollution and psychological well-being among urban residents in Guangzhou, China. *Science of The Total Environment*, *711*, 134843.

Wiesenfeld, E. (1987). Residential density, locus of control, and crowding perception in popular housing projects. *Journal of Environmental Psychology*, *7*, 143–158.

Wood, E., Harsant, A., Dallimer, M., Cronin de Chavez, A., McEachan, R. R., & Hassall, C. (2018). Not all green space is created equal: Biodiversity predicts psychological restorative benefits from urban green space. *Frontiers in psychology*, *9*, 2320.

Wu, W., Chen, Y., & Liu, Y. (2020). Perceived spillover effects of club-based green space: Evidence from Beijing golf courses, China. *Urban Forestry & Urban Greening*, *48*, 126518.

Wu, W., Dong, G., Yeran, S., & Yun, Y. (2020). Contextualized effects of park access and usage on residential satisfaction: A spatial approach. *Land Use Policy*, *94*, 104532.

Wu, W., Yao, Y., Song, Y., He, D., & Wang, R. (2021). Perceived influence of street-level visible greenness exposure in the work and residential environment on life satisfaction: Evidence from Beijing. *China. Urban Forestry & Urban Greening*, *62*, 127161.

Xie, B., An, Z., Zheng, Y., & Li, Z. (2018). Healthy aging with parks: Association between park accessibility and the health status of older adults in urban China. *Sustainable Cities and Society*, *43*, 476–486.
Xue, F., Gou, Z., & Lau, S. S. Y. (2016). Human factors in green office building design: The impact of workplace green features on health perceptions in high-rise high-density Asian cities. *Sustainability*, *8*, 1095.
Zhang, K. H., & Song, S. (2003). Rural–urban migration and urbanization in China: Evidence from time-series and cross-section analyses. *China Economic Review*, *14*(4), 386–400.
Zhong, J., Li, Z., Sun, Z., Tian, Y., & Yang, F. (2020). The spatial equilibrium analysis of urban green space and human activity in Chengdu, China. *Journal of Cleaner Production*, *259*, 120754.
Zhou, B., Zhao, H., Puig, X., Xiao, T., Fidler, S., Barriuso, A., & Torralba, A. (2019). Semantic understanding of scenes through the ade20k dataset. *International Journal of Computer Vision*, *127*, 302–321.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Wang, R., Yang, L., Yao, Y., & Wu, W. (2022). Exploring the association between neighbourhood streetscape vegetation and subjective well-being in a high-density built environment: Evidence from Beijing, China. *Health & Social Care in the Community*, *00*, 1–13. https://doi.org/10.1111/hsc.13968