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Exploring the nonlinear effects of greenery on active travel among the ageing population

Ruoyu Wang [a], Jiaying Zhang [b,c,d], Dongwei Liu [e], Yao Yao [f], Mengqiu Cao [g,*]

[a] Institute of Public Health and Wellbeing, University of Essex, Essex, United Kingdom
[b] Guangzhou Urban Planning and Design Survey Research Institute Co. Ltd., Guangzhou, China
[c] Collaborative Innovation Centre for Natural Resources Planning and Marine Technology of Guangzhou, Guangzhou, China
[d] Guangdong Enterprise Key Laboratory for Urban Sensing, Monitoring and Early Warning, Guangzhou, China
[e] Department of Architecture and Civil Engineering, City University of Hong Kong, Hong Kong, China
[f] School of Geography and Information Engineering, China University of Geosciences, Wuhan, China
[g] Bartlett School of Environment, Energy and Resources, University College London, London, United Kingdom

A R T I C L E I N F O

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A B S T R A C T

This paper examines the nonlinear influences of the quantity and quality of street-level greenery on active travel among older adults. The active travel information was obtained from the Study on Global Ageing and Adult Health conducted in Shanghai, China. Street-level greenery was assessed based on street view data and a deep learning approach, namely street view greenery quantity (SVG-quantity) and quality (SVG-quality). Gradient boosting decision tree models and SHapley Additive exPlanations were applied. The results showed that SVG-quantity had a positive and nonlinear link with active travel. However, SVG-quality was positively correlated to the propensity for active travel, but the association became inverse when SVG-quality exceeded a specific cut-off point. SVG-quality also had a nonlinear and positive association with the duration of active travel. This research demonstrates the importance of improving the provision of street-level greenery in urban areas, which is crucial for facilitating active lifestyles among the ageing population.

1. Introduction

In recent years, an ageing population has become a serious issue in China (Feng et al., 2020), and the number of older people has increased dramatically in comparison to that of other developing countries (World Health Organization, 2015). According to the China Statistical Yearbook, there were 158 million older adults aged over 65 in 2017, and the number is estimated to rise to nearly 366 million by 2050 (National Bureau of Statistics of China, 2018). Therefore, more attention should be paid to the ageing population in the Chinese context.

Engaging in daily physical activity (PA) can have many health benefits, such as a lower risk of mortality (Wen et al., 2014) and cardiovascular disease (Lachman et al., 2018). However, although the weighted prevalence of physical inactivity slightly decreased among the Chinese ageing population from 2010 (22 %) to 2015 (20 %) (Li et al., 2020), still only about half of the Chinese ageing population achieved the PA level recommended by the WHO (defined as ≥150 min of moderate-intensity PA) in 2015 (He et al., 2021). Active travel (e.g., walking) offers an effective means of increasing people's energy expenditure (Wang et al., 2020), thus contributing to better health (Lee and Buchner, 2008), and decreasing the amount of air pollution and noise resulting from traffic (Rabl and de Nazelle, 2012). Therefore, understanding how street greenery affects active travel has important implications for healthy ageing (John et al., 2023).

Urban greenery is increasingly recognised as playing an important role in encouraging active travel among residents living in neighbourhood environments (Lu et al., 2018, 2019). Urban greenery in parks and on streets can help to offer a pleasant outdoor space for active travel (Ao et al., 2019, 2020; Lu et al., 2019). Thus, people are more willing to choose active travel in greener neighbourhoods (Ta et al., 2021; Wang et al., 2023). Furthermore, the positive effect of active travel within an environment in which urban greenery features may result in more physiological and psychological health benefits in comparison with other types of urban environments (Thompson Coon et al., 2011). However, existing literature on the link between greenery and active travel has been mainly based on regression models, and therefore, it

* Corresponding author.
E-mail addresses: rw24347@essex.ac.uk (R. Wang), dongweiliu3-c@my.city.edu.hk (D. Liu), Yaoy@cug.edu.cn (Y. Yao), mengqiu.cao@ucl.ac.uk (M. Cao).

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neglects the potential nonlinear effects of greenery on modes of travel (Yang et al., 2021a). In addition, most existing literature has only shed light on the impact of larger areas of general greenery (e.g., parks), while scant attention has been paid to street-level greenery (Lu et al., 2018, 2019).

Therefore, this study aims to examine the nonlinear influences of street-level greenery quantity and quality on active travel among older adults in the Chinese context. The methods used in this study could enrich the existing literature in several respects. First, this study investigates the link between street-level greenery and active travel in a developing country context, where levels of active travel may be inadequate, and cities are denser than in many developed countries. Second, we use both SHapley Additive exPlanations (SHAP) and gradient-boosting decision trees (GBDT), which are explainable artificial intelligence methods, to gain insights into the nonlinear effects of street-level greenery on active travel. This is significant as the results obtained in relation to these nonlinear effects can provide us with useful information regarding the optimal intervention threshold of greenery. Third, we pay attention to the impact of both the quality and quantity of street-level greenery using street view data, which could help to further our understanding of the beneficial effect of street-level vegetation. Lastly, rather than focusing on the general population, we shed new light on active travel among the ageing population, as they may be more vulnerable and engage in less PA than other population groups.

2. Literature review

Existing evidence has suggested that features of the urban neighbourhood environment play a crucial role in determining which modes of travel people use (Ding et al., 2017; Eldeeb et al., 2021; Guo and He, 2021a, 2021b; Wang and Zhou, 2017; Ye and Titheridge, 2017). Among various factors connected with the built environment in urban neighbourhoods, greenery has attracted significant attention in the literature, as it is an aspect that policymakers can address relatively easily through interventions, thus enabling them to maximise the positive effects of greenery through urban planning policy (Douglas et al., 2017; Browning et al., 2022; Wolch et al., 2014). For example, Hogendorf et al. (2020) showed that the accessibility of neighbourhood greenery was positively related to recreational active travel, but negatively linked with active commutes, in the Netherlands. Sugiyama et al. (2013) also suggested that neighbourhood greenery was related to an increase in walking among residents in Adelaide, Australia. Zhang et al. (2020) documented that the size of parks was associated with a pronounced increase in walking in the UK. Meanwhile, Cole-Hunter et al. (2015) found that the quantity of urban greenery was positively linked to the likelihood of people commuting by bicycle in Barcelona, Spain. Lu et al. (2019) suggested that street greenery, rather than greenery in general (normalised difference vegetation index), was positively related to the likelihood of cycling in Hong Kong. Several links between greenery and active travel have been established (Dong et al., 2023). First, there has been an increase in studies investigating the mitigating role of residential vegetation in relation to environmentally hazardous factors (Ba and Kang, 2019; Nowak et al., 2006). Existing studies have confirmed that the likelihood of individuals choosing active travel is higher in a nicer environment (e.g. less air pollution) (An et al., 2019; MacNaughton et al., 2014). Second, greenery is an important natural feature of the environment that can have a restorative effect on travellers, by helping them to feel more relaxed and reducing stress (Jiang et al., 2021). Thus, it can provide walkers or cyclists with a better travelling experience and significantly improve their travel satisfaction (Ta et al., 2021), which may further encourage them to commit to active modes of travel. Third, some scholars have argued that urban greenery, and street greenery in particular, can provide travellers with shade, thereby offering them protection from strong sunlight or, conversely, shelter from rain (Aleksandrowicz and Pearlmutter, 2023; Krenn et al., 2014). This aspect is particularly important for active travellers, as it may be difficult for them to find shelter during their journey (Lu et al., 2018).

This study is related to the increasing body of literature exploring the nonlinear relationships between physical environments and modes of travel (Gao et al., 2023). However, only a few studies have paid attention to the nonlinear impacts of urban greenery on active travel among the ageing population (Yang et al., 2021b; Yang et al., 2022a, 2022b; Zang et al., 2023). For example, Yang et al. (2021a) showed that when there is a moderate amount of vegetation, it can encourage older adults to take more walks; however, if the amount of greenery exceeds a certain threshold, the link between the two diminishes. Zang et al. (2023) found that street-level greenery may have a greater impact on walking among the ageing population than NDVI, although both have a beneficial effect within a certain range, but a detrimental effect beyond this range. There are several potential explanations for the nonlinear associations between greenery and active travel. First, existing evidence has confirmed that there is a dose-response effect regarding the restorative function of urban greenery, which means that travellers may only benefit from its restorative effects within a certain range (Jiang et al., 2014). Second, regarding the role that greenery plays in mitigating environmental hazards such as air pollution, the effect of the density of greenery has also been shown to be nonlinear (Hao et al., 2022). This is because, when greenery becomes denser, its capacity to block air pollutants significantly increases (Hao et al., 2022). Third, previous studies have shown that residents' subjective perceptions of natural elements do not change in a linear fashion with an increase in the provision of greenery (Suppakittpaisarn et al., 2019). For example, Suppakittpaisarn et al. (2019) suggested that the density of greenery is positively correlated to a subjective preference for the environment, and the relationship may also be depicted in the form of a nonlinear curve.

It is widely acknowledged that neighbourhood streets tend to be the most popular context for recreational walking (Rosenberg et al., 2010). However, evidence regarding the effect of street-level greenery on active travel is insufficient, as most of the existing evidence is based on the provision of general urban greenery, such as accessibility to parks or NDVI (Lu et al., 2019). This is mainly due to the technical limitations of the research methods available. Traditional methods of assessing street-level greenery mainly rely on either field audits or self-reported questionnaires, both of which are labour-intensive (Lu et al., 2019). With the progress made by and increasing use of mapping services in recent years, street view data has begun to attract researchers' attention because of its potential for environmental monitoring, especially in the case of urban greenery (Kang et al., 2020). For example, Wang et al. (2021) applied a convolutional network using street-view data to quantify street-level greenery. Hence, although some studies have pointed out that the quantity of greenery may be less important than the quality of greenery in influencing people's behaviour and well-being, there is still not enough evidence to make any conclusive statement about the effect of the quality of greenery (Wang et al., 2021). As well as calculating the quantity of street-level greenery, the method and data described above can also be used to shed light on the quality of greenery (Wang et al., 2021). For instance, Wang et al. (2021) applied both street-view images and deep-learning methods to develop an effective approach for evaluating the quality of street-level greenery.

3. Data and methods

3.1. WHO study on global ageing and adult health (SAGE) in shanghai

We used the 2010 WHO Study on Global Ageing and Adult Health (SAGE) conducted in the city of Shanghai, China, to carry out the analysis. A sample of middle-aged and older adults (aged >50) living in Shanghai was chosen via multistage random cluster sampling. The selection of administrative districts, streets, and towns was determined based on the likelihood of being picked, which was computed using the number of households and the size of the region. The detailed sampling procedure can be found in the supplementary file, which also explains how the SAGE team ensure that the samples are representative. The final SAGE-Shanghai dataset comprised 9524 residents from 40 neighbourhoods (*juweihui*) in the five sampled districts (Luwan, Hongkoui, Qingpu, Minhang and Nanhui). After excluding individuals aged below 60 with missing information about transportation and neighbourhood location, we were left with 4395 valid samples. Detailed information on SAGE can be found in Wu et al.'s (2015) study.

3.2. Active travel

First, the propensity for active travel was measured by a self-reported question. Respondents were asked if they had walked or cycled to get to and from places (for at least 10 min continuously). The possible answers were a binary choice of either '0 = no' or '1 = yes'. Second, the duration of active travel was measured by two self-reported questions. Respondents were required to report the daily duration (minutes) and weekly frequency (days) of their active travel behaviours (walking/cycling to get to or from places). The duration of active travel per week was calculated by multiplying the daily duration by the weekly frequency.

3.3. Street-level greenery quantity and quality

The 2013 street view data was used for quantifying street view greenery (SVG-quantity). Tencent Map, the most popular mapping service in China, provided the images. We sourced images from specific locations along the network of roads (at 100 m intervals) selected from OpenStreetMap (Haklay and Weber, 2008). All the sampling points were randomly chosen from across the study region. Altogether, 38,239 sampling points were created for downloading the street view images, and four images (0 to 270 degrees) were taken at each location. Building on existing research (Wang et al., 2021), SVG-quantity was determined from the ADE20K (Zhou et al., 2019) by utilising the FCN-8 s network (Long et al., 2015). The efficacy of this technique for distinguishing street-level vegetation from street-view images has been well established (Wang et al., 2022). The SVG-quantity per image was then computed by dividing the sum of the pixels containing greenery (vegetation) by the total number of pixels. Finally, the SVG-quantity of each neighbourhood was determined by taking the average values of all the images within a 1000-m radius.

Regarding the SVG-quality, following the criteria for greenery quality scores developed by Van van Dillen et al., 2012, we randomly chose 2000 images to build the training dataset and assigned each of them a score from 0 to 10 based on the following ten different characteristics (Table S1: safety, shelter, accessibility, maintenance, absence of litter, variation, colourfulness, naturalness, clear arrangement, and general impression). All the scores achieved a high level of internal consistency (Table S2: internal consistency ≥ 0.85). We then applied the random forest (RF) model (Breiman, 2001) to automate the scoring process, and the training was conducted by correlating the scores of each attribute of the quality of greenery with the distribution of ground-level elements from the results of the image segmentation. Once the RF model had been trained, we applied it to evaluate the 10 characteristics of greenery in the 38,239 samples. Based on existing studies (Wang et al., 2021), the average values of all ten attributes (Cronbach's alpha>0.80) were used for evaluating the quality of the greenery in each image. The average score of all the images within the 1000 m buffer was calculated to determine the SVG-quality for each neighbourhood. More details can be found in Wang et al.'s (2021) study.

3.4. Covariates

Following existing literature (Lu et al., 2018, 2019; Yang et al., 2021a, 2021b), several socio-demographic variables were controlled for: age, marital status, gender, education, annual income per capita (Chinese Yuan), employment status, whether respondents smoke and whether they drink alcohol and, if so, how much. We also assessed 'functional limitations', using a questionnaire containing 22 items (Table S2), designed to evaluate the difficulties that respondents encountered in doing daily activities. Most of the respondents answered 'None' to all the questions, so we treated 'functional limitations' as a binary variable (1 = other, 0 = answered 'None' to all questions). In addition, to control for the residential self-selection bias (Cao et al., 2009; Guan et al., 2020; van Wee and Cao, 2022) to some extent, we included perceived safety when walking, and duration of residency. Perceived safety when walking can be used to reflect older adults' attitudes towards active travel, while the duration of residency can be used to control for residential self-selection bias, as movers are more likely to be influenced by self-selection bias than non-movers (Wu et al., 2021).

The neighbourhood-level built environment covariates: urbanity, population density (persons/km^2), connectivity of intersections (numbers/km^2) and index of land use mix (0–1) were adjusted following the method used by Frank et al. (2006). The proximity to the nearest metro station (m) was also included as a proxy for the presence of large elements of transport infrastructure. In addition, the following covariates were also used following existing studies (Yang et al., 2024): the density of bus stops (numbers/km^2), the slope of the terrain (degree), and the average annual level of $PM_{2.5}$ ($\mu g/m^3$). Details can be found in the supplementary file.

The neighbourhood deprivation index (NDI) was also calculated for each neighbourhood in Shanghai. We used four census indicators (unemployment rates, home-ownership rates, low-status occupations, and low levels of education) and carried out principal component analysis to synthesise the NDI (Sampson et al., 2002; Wang et al., 2022). The higher the NDI, the more deprived the neighbourhood. The neighbourhood-level built environment covariates listed above were all calculated within a 1000-m radius of the respondents' neighbourhoods. Table 1 presents a summary of the descriptive statistics.

4. Method

4.1. GBM model

We used a gradient boosting machine (GBM) (Friedman, 2001) to model the nonlinear effects of the quantity and quality of street-level greenery on active travel among Chinese older adults. GBMs are widely used to investigate the nonlinear impacts of the built environment on people's travel behaviours (Ding et al., 2018). The major advantage of the tree-based GBM is that it tends to produce a better goodness-of-fit than a normal regression model and can provide information about the shape of the impacts among the predictors and the outcomes (Hagenauer and Helbich, 2017). For example, they were visually represented, in order to establish what kind of shape they would take. The GBM method generally yields relatively small residuals because it calculates the loss function of the model using a gradient boosting algorithm, and the model is finalised when the residuals for each tree reach their potential minimum value (Ding et al., 2018). The residuals for each tree are then added up to calculate the overall residuals (Ding et al., 2018). The trees are normally in different forms, and they are aggregated to form a single aggregated model in a sequential process (Elith et al., 2008), which enables the GBM to model different types of outcomes and produce a nonlinear coefficient for different predictors. The GBM is superior to the traditional regression model for use in a transport-related context in several respects (Yang et al., 2022a, 2022b). First, it can achieve a high level of accuracy in predicting the outcome, as it is based on a combination of multiple trees which enables the model to construct a complex relationship between the predictors and the outcomes (Friedman, 2001). Second, the GBM does not require the data to be in a certain form or to be normally distributed, so multicollinearity problems with the predictors or missing values will result in less bias than is the case for traditional linear regression models.

Table 1
Statistical summary of the predictors.

Variables	Mean value (SD) / Proportion
Active Travel	
Yes	0.48
No	0.52
Weekly duration of active travel (minutes)	140.51 (372.26)
Car ownership	
Yes	0.18
No	0.82
Motorbike	
Yes	0.73
No	0.27
Urbanness	
Urban area	0.53
Rural area	0.47
Gender	
Male	0.48
Female	0.52
Age group (years)	
60–69	0.52
70–79	0.35
≥80	0.13
Educational attainment	
Primary school and below	0.59
High school	0.32
College and above	0.09
Marital status	
Married	0.80
Other	0.20
Employment	
Employed	0.15
Other	0.85
Annual household income per capita (Chinese Yuan)	18,922.78 (81,698.21)
Functional limitation	
Yes	0.09
No	0.91
Safety (1–5)	3.57 (0.92)
Duration of residency (years)	
≥5	0.97
<5	0.03
$PM_{2.5}$ (μg/m^3)	54.81 (3.98)
NDI	0.44 (1.79)
Neighbourhood population density (persons/km^2)	30,309.12 (37,092.80)
Index of land use mix	0.15 (0.03)
Connectivity of intersections (numbers/km^2)	40.50 (38.16)
Bus stop density (numbers/km^2)	1.12 (1.81)
The slope of the terrain (degree)	2.26 (1.29)
Access to metro station (m)	5813.64 (6989.67)
SVG-quantity (0–1)	0.19 (0.09)
SVG-quality (0–1)	0.62 (0.08)

Third, the GBM ranks the predictors in terms of their relative importance, thus enabling comparisons to be made between different predictors in different units. Hence, the GBM does not assume that the predictors and outcomes are linear, so its predictive ability can provide researchers with information about nonlinear associations between the predictors and outcomes.

With regard to the propensity for active travel model, we used the "Bernoulli" linked function because the outcome is a binary variable. The following three parameters were tuned for the GBM: the number of trees; the maximum depth of a tree; and the minimum number of observations in the terminal nodes of the trees. In order to optimise the GBM, we followed previous studies (Yang et al., 2021a, 2021b) and applied the searching in grids method (Claesen and De Moor, 2015). During the first stage, we determined the scope of all the parameters (the number of trees: from 100 to 1000 with an interval of 100; the maximum depth of a tree: from 1 to 10; and the minimum number of observations in the terminal nodes of the trees: from 5 to 15). The next step involved estimating 1000 (=10*10*10) possible combinations of the three parameters and testing the goodness-of-fit based on a five-fold cross-validation method (Ridgeway, 2007). After conducting 1000 tests, we found that the GBM with the best performance was the following: number of trees = 982; maximum depth of a tree = 8; and minimum number of observations = 6. With regard to the final GBM, the root mean square error (RMSE) was 1.11, while the Pseudo R^2 value was 0.72.

For the duration of active travel model, we used the "Gaussian" linked function because the outcome is a continuous variable. Based on existing studies (Tao et al., 2020), we set the minimum number of observations as 10 and started testing the depth of trees from 1 to 49, using 5000 trees. We again used the 5-fold cross-validation to find the optimum parameter which would produce the lowest RMSE. The lowest RMSE was found to occur when the tree depth was 35, and the number of trees was 1137. The final root mean square error (RMSE) was 344.24, while the Pseudo R^2 value was 0.15.

4.2. SHapley additive exPlanation (SHAP) value

Existing machine learning techniques, including GBM, are black boxes as they cannot interpret the system's structure. Lundberg and Lee (2017) and Lundberg et al. (2020) proposed the SHAP approach using game theory to interpret machine learning. The SHAP approach offers a more comprehensive analysis of the importance of different predictors, which cannot be effectively captured by the traditional machine learning approach. In other words, the black box here means that the GBM itself can only display the association without explaining how such an association is estimated, while the SHAP gives a more transparent way of quantifying this association. In this model, the SHAP value was utilised to determine the predictive power of different independent variables, by employing the average absolute SHAP values. Combining machine learning techniques (i.e. GBM) with the SHAP method can offer a way of revealing the relative importance of predictors, non-linear associations, thresholds, and interactions between variables.

We used two methods to visually represent the results: calculating the relative importance of different predictors using the SHAP; and plotting their partial dependence. The relative importance of a predictor was calculated in terms of its mean contribution to predicting the overall outcome of all the trees. A partial dependence plot (PDP) displays the predicted value of the outcome with a certain value assigned to a chosen predictor (Hastie et al., 2009). After adjusting for the covariates, the PDPs were used to show the nonlinear impact of SVG on the propensity for and duration of active travel (SHAP values). The results of the PDPs for the actual values of the outcomes were also provided as a reference (see supplementary file). The analysis was conducted using the "gbm" (Ridgeway, 2007), and "shapviz" (Lundberg and Lee, 2017) packages via R 3.6.3.

5. Results

Fig. 1 and Table 2 show the relative importance of each variable in predicting the propensity for and duration of active travel. With regard to the summary plot for SHAP, the low SVG-quantity values (purple dots) were mainly on the left side, while the high values (orange dots) were mostly on the right. This means that SVG-quantity was positively associated with a propensity for active travel (Fig. 1a). Similar results were observed for the duration of active travel, which suggests that SVG-quantity was positively related to the duration of active travel (Fig. 1b). In addition, regarding the propensity for active travel, low SVG-quality values (purple dots) were mainly distributed on the right, which means they were generally negatively related to the propensity for active travel (Fig. 1a). However, as for the duration of active travel, the low SVG-quality values (purple dots) were mainly on the left-hand side, while the high values (orange dots) were mostly on the right, which suggests that SVG-quality was positively linked to the duration of active travel (Fig. 1b).

With regard to the contribution of different predictors (Table 2), first, SVG-quantity contributes the most (27.65 %), while SVG-quality contributes about 2.81 % to predicting the propensity for active travel. Overall, transport-related built environment factors, including the index

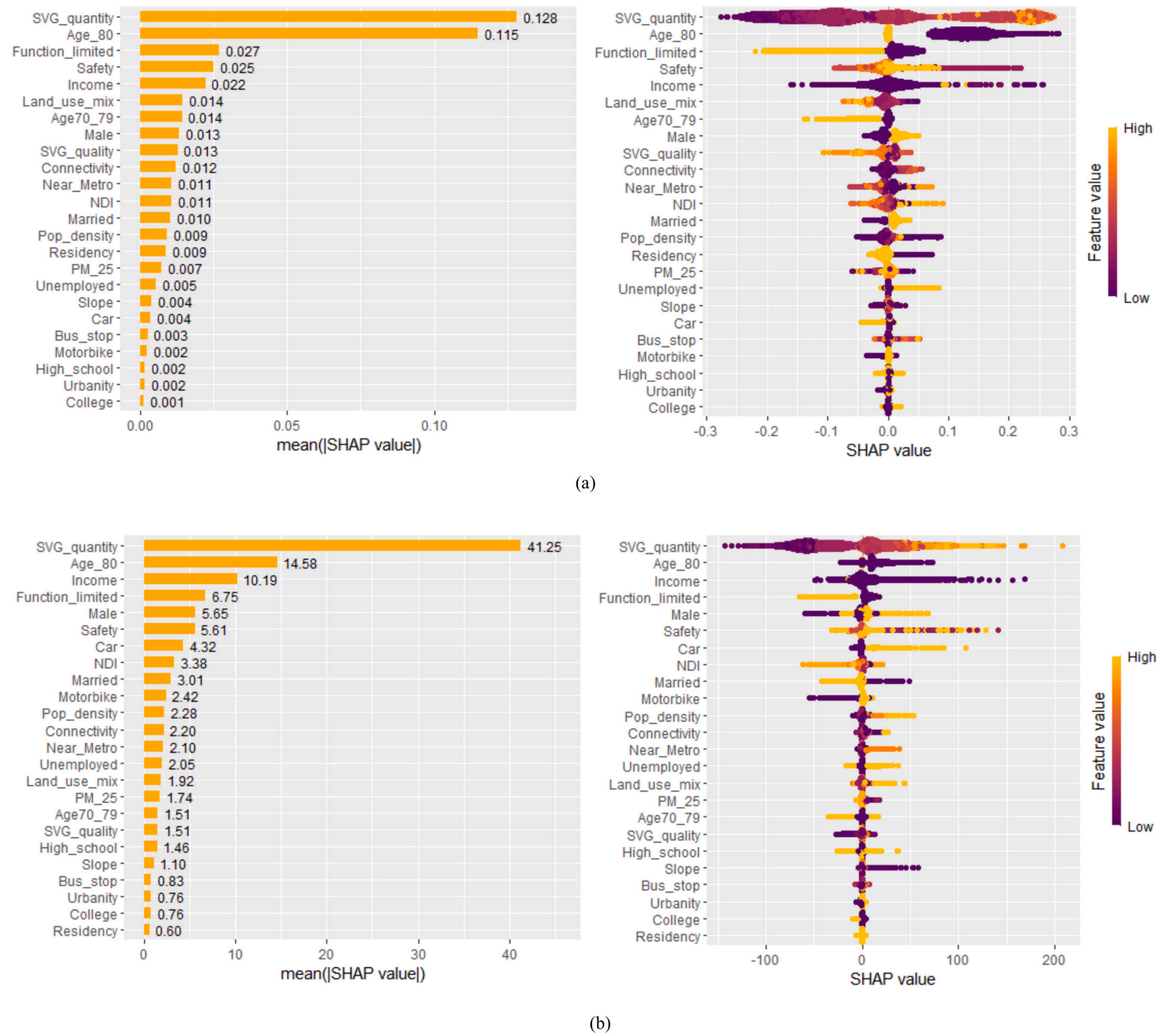

Fig. 1. Relative importance and SHAP summary plot of different variables in predicting active travel: (a) propensity for active travel; (b) duration of active travel.

of land use mix, the density of bus stops, the connectivity of intersections, the slope of the terrain, and the distance to the nearest metro station, contribute nearly 12.96 % to predicting the propensity for active travel. Second, SVG-quantity contributes 34.96 % and SVG-quality contributes approximately 1.28 % to predicting the duration of active travel. Overall, transport-related built environment factors contribute nearly 10.32 % to predicting the duration of active travel.

The PDP illustrates the relationships between the SVG and the propensity for and duration of active travel. Fig. 2 shows the association between the SVG and the propensity for active travel after adjusting for the covariates. First, SVG-quantity was generally positively related to the propensity for active travel (Fig. 2a). However, this association reached saturation point when the index was over 0.25. Second, SVG-quality was positively linked to the propensity for active travel when it was less than 0.65, but once the value exceeded the cut-off point, the association became inverse (Fig. 2b). Third, SVG-quantity was generally positively related to the duration of active travel (Fig. 2c). Fourth, SVG-quality was generally positively related to the duration of active travel, but this association reached saturation point when the index was over 0.55 (Fig. 2d).

Fig. 3 shows the association between a series of important neighbourhood-level covariates and the propensity for active travel. First, the population density was generally positively associated with the propensity for active travel (Fig. 3a). Second, the land use mix index was generally negatively linked to the propensity for active travel (Fig. 3b). Third, the connectivity of intersections had no statistically significant effect on the propensity for active travel when its value was below 62.5/km^2 (Fig. 3c). However, when it was over 62.5/km^2, the association with the propensity for active travel became positive. When the value was over 100 km^2 the association reached saturation point. Fourth, the density of bus stops was negatively related to the propensity for active travel when it was less than 2/km^2, but once it exceeded 2/km^2, the effect became positive (Fig. 3d). Finally, the distance to the nearest metro station was negatively related to the propensity for active travel when it was less than 12.5 km (Fig. 3e), but the association became positive when the distance to the nearest metro station was greater than 12.5 km.

Fig. 4 illustrates the association between a series of important

Table 2
The percentage contribution and rankings of the variables.

	Variables	Active_travel_propensity			Active_travel_duration		
		Mean (|SHAP| value)	% Contribution	Rank	Mean (|SHAP| value)	% Contribution	Rank
Travel behaviour			1.30			5.71	
	Car	0.004	0.86	19	4.32	3.66	7
	Motorbike	0.002	0.43	21	2.42	2.05	10
Socio-demographic variables			52.48			44.22	
	Income	0.022	4.75	5	10.19	8.64	3
	Male	0.013	2.81	8	5.65	4.79	5
	Age70_79	0.014	3.02	7	1.51	1.28	17
	Age_80	0.115	24.84	2	14.58	12.36	2
	Married	0.010	2.16	13	3.01	2.55	9
	High_school	0.002	0.43	22	1.46	1.24	19
	College	0.001	0.22	24	0.76	0.64	23
	Unemployed	0.005	1.08	17	2.05	1.74	14
	Function_limited	0.027	5.83	3	6.75	5.72	4
	Safety	0.025	5.40	4	5.61	4.76	6
	Residence	0.009	1.94	15	0.6	0.51	24
Social environment			2.81			3.51	
	NDI	0.011	2.38	12	3.38	2.86	8
	Urbanness	0.002	0.43	23	0.76	0.64	22
Built environment			12.96			10.32	
	Pop_density	0.009	1.94	14	2.28	1.93	11
	Connectivity	0.012	2.59	10	2.2	1.86	12
	Land_use_mix	0.014	3.02	6	1.92	1.63	15
	Bus_stop	0.003	0.65	20	0.83	0.70	21
	Near_Metro	0.011	2.38	11	2.1	1.78	13
	Slope	0.004	0.86	18	1.1	0.93	20
	PM_25	0.007	1.51	16	1.74	1.47	16
Green space			30.45			36.24	
	SVG_quantity	0.128	27.65	1	41.25	34.96	1
	SVG_quality	0.013	2.81	9	1.51	1.28	18

neighbourhood-level covariates and the duration of active travel. First, population density was negatively related to the duration of active travel when it was less than 50,000 persons/km^2 (Fig. 4a). However, when it was over 50,000 persons/km^2, the association with the duration of active travel became positive. Second, when the index of land use mix was less than 0.20, it was negatively associated with the duration of active travel (Fig. 4b). However, when it exceeded 0.20, the association with the duration of active travel became positive. Third, the connectivity of intersections was negatively related to the duration of active travel when it was less than 50/km^2, but once the value exceeded 50/km^2, the association became inverse (Fig. 4c). Fourth, bus stop density was negatively linked to the duration of active travel if it did not exceed 2/km^2, but the association became inverse when the value exceeded 2/km^2 (Fig. 4d). Finally, the impact of the distance to the nearest metro station on the duration of active travel was negative when its value was less than 10 km (Fig. 4e). However, when the value exceeded 10 km, the association with the duration of active travel became positive.

6. Discussion

This study contributes to current knowledge about the nonlinear association between urban greenery and active travel in several respects. First, it investigates the link between street-level greenery and active transport in a densely populated city within a developing country. Second, it systematically explores the nonlinear associations between active travel and street-level greenery using the SHAP values. Third, it is the first study to examine the effects of both the quantity and quality of street-level greenery using street view data, which can help to further our understanding of the beneficial effect of street-level vegetation. Therefore, our work can contribute to existing theories about associations between the environment and travel behaviour from the perspective of nature-based solutions. Finally, it offers new insights into active travel among older adults, thus contributing to promoting healthy cities and healthy ageing policies.

6.1. *Interpretation of the main findings*

Based on the results of the GBM models and SHAP values, SVG-quantity contributes most to predicting active travel in older adults. On the one hand, this may imply that greenery plays an important role in older adults' travel behaviour. On the other hand, it may simply imply that there is a mathematical association between the predictor and outcome, so the observed association may be because there is more visible greenery in communities where older adults are more active travellers. SVG-quantity was also found to be much more important in terms of predicting the propensity for and duration of active travel than SVG-quality. There are several potential explanations for this finding. First, older adults' visual abilities may not be as good as those of younger adults (Taylor et al., 2016). SVG-quality is significantly related to the presence of some smaller elements within the environment (e.g., flowers) and the colourfulness of ground objects (Wang et al., 2021). Therefore, the ageing population may not be able to identify small natural elements on the street due to poorer visual ability, and this may weaken the effect of SVG-quality on them. However, SVG-quantity mainly measures the level of greenness, which usually occupies a larger proportion of the visual field, so this may be less influenced by older adults' visual abilities. Second, the ageing population in China tend to engage in active travel mainly for recreational purposes rather than commuting (Taylor et al., 2016). Existing studies have shown that travelling for recreational purposes is much less stressful than commuting (Liu et al., 2022a, 2022b). Thus, as the restorative effect of SVG-quality may be greater for people with higher stress levels (Liu et al., 2022a, 2022b), the restorative benefits of SVG-quality could be weaker for the ageing population if they are undertaking active travel for recreational purposes.

This study showed that the link between SVG and active travel is nonlinear. More specifically, SVG-quantity was generally positively linked to the propensity for and duration of active travel. We found that the effect of SVG-quantity became saturated when the value was over 0.25. A possible explanation for this phenomenon is that when the

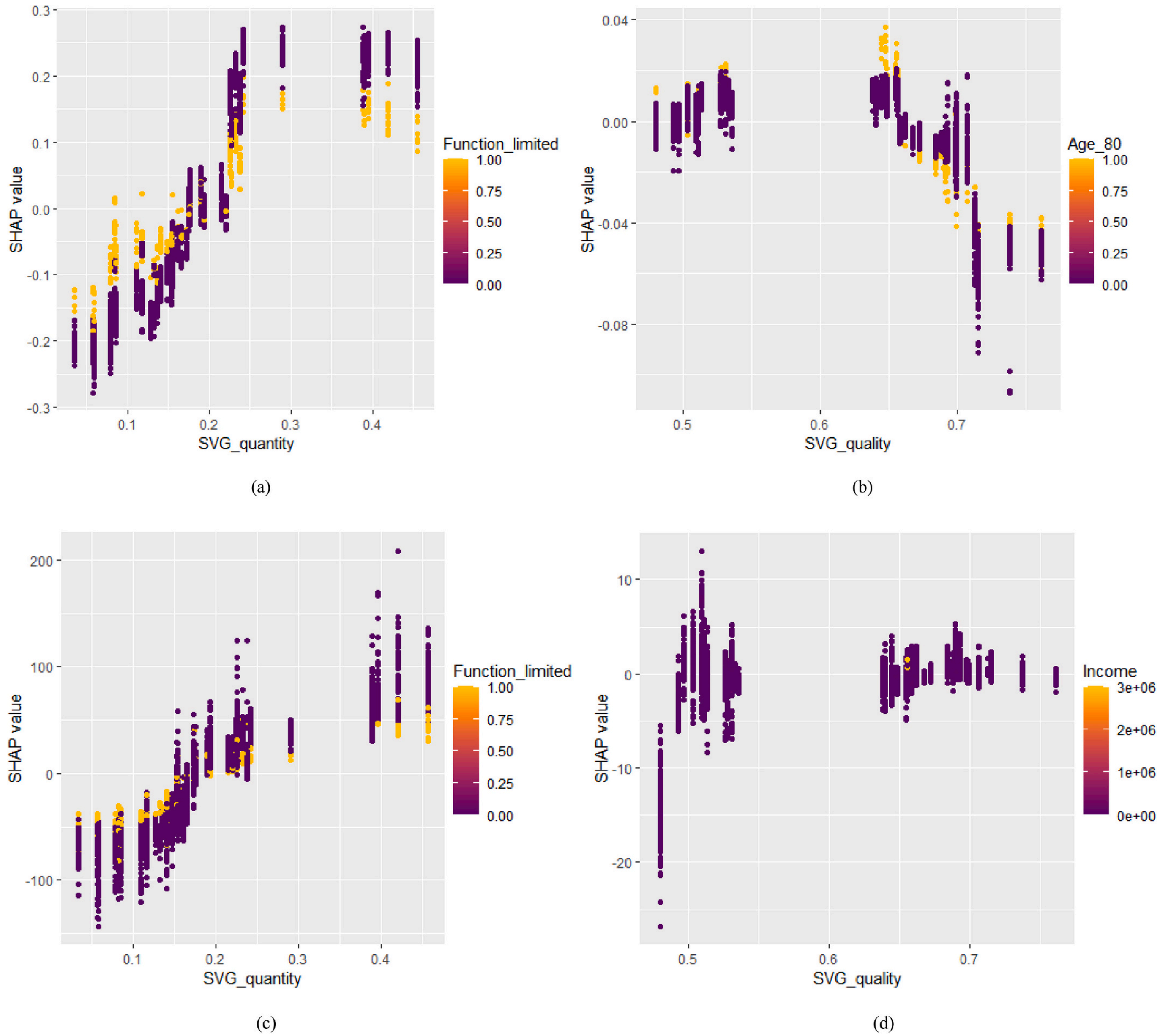

Fig. 2. Non-linear impacts of street-level greenery on active travel: (a) SVG-quantity and propensity for active travel; (b) SVG-quality and propensity for active travel; (c) SVG-quantity and duration of active travel; (d) SVG-quality and duration of active travel.

proportion of visible greenery is over 25 %, people may not be able to identify significant differences in colour which may limit the restorative benefits of vegetation (Jiang et al., 2014). However, when the value was below 0.25, SVG-quantity was positively related to active travel. This may be because a higher level of SVG-quantity is associated with less air pollution and noise (Wang et al., 2020), which may improve the outdoor environment and further encourage more active travel. Second, as SVG-quantity is measured based on the presence of street-level vegetation, it can also reflect the level of shade provision within neighbourhoods (Li et al., 2018). Therefore, members of the ageing population are less likely to have to worry about strong sunlight if they live in neighbourhoods with higher SVG-quantity. Third, it has been observed in existing literature that street-level vegetation is positively associated with restorative effects (Jiang et al., 2014), so neighbourhoods with higher SVG-quantity may provide a more pleasant and relaxing environment for the ageing population to walk or cycle in.

With regards to SVG-quality, the results showed that initially it was positively associated with active travel; however, the association then became inverse when SVG-quality exceeded the cut-off point (0.65). On the one hand, SVG-quality determines the restorative effect of green space, which has a proven link with active travel behaviour (Jiang et al., 2014). SVG-quality also reflects people's perceptions of the safety of green spaces (Wang et al., 2021), and previous literature has documented that people are more willing to walk when they perceive the neighbourhood environment to be safer (Leslie et al., 2010). On the other hand, existing studies suggest that higher green space quality is associated with reduced psychophysiological fatigue among car drivers (Xu et al., 2024). Consequently, older adults living in neighbourhoods with higher SVG-quality (over 0.65) may still experience restorative benefits even while driving. As a result, they may be less inclined to walk and more likely to opt for faster travel mode.

Other built environment factors also had associations with active travel among older adults. First, the population density was positively associated with active travel. Neighbourhoods with a higher population density may have more recreational facilities within walking distance (Lu et al., 2017), so older adults in these neighbourhoods are more likely

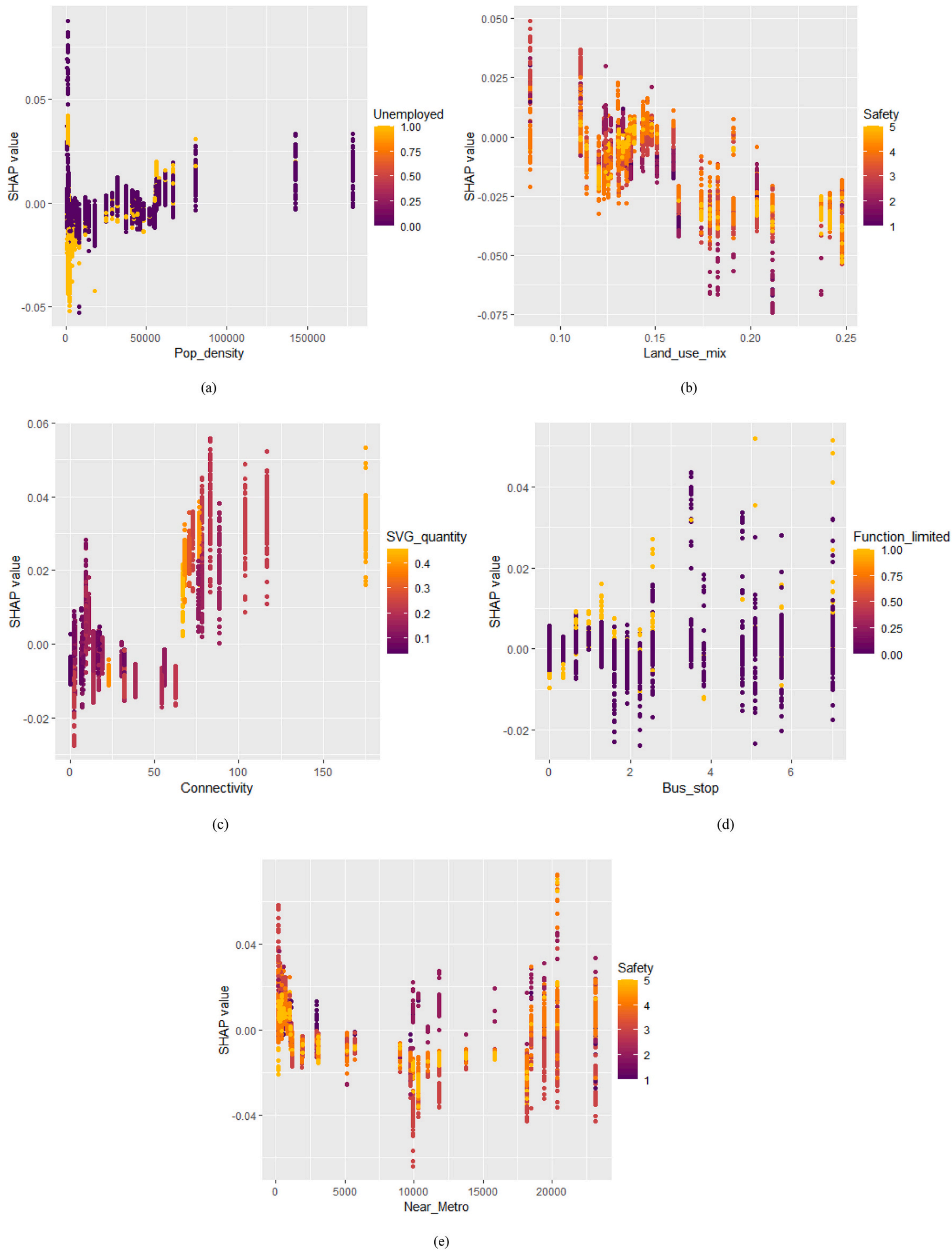

Fig. 3. Non-linear impacts of built environment predictors on the propensity for active travel: (a) Neighbourhood population density; (b) Index of land use mix; (c) Connectivity of intersections; (d) Density of bus stops; (e) Distance to the nearest metro station.

to walk to their destinations. Second, the land use mix index was negatively related to active travel, which is inconsistent with existing findings (Forsyth et al., 2007; Lu et al., 2017). A possible explanation for this is that a higher land use mix indicates a greater diversity of destinations within a neighbourhood (Lu et al., 2017), but this may also suggest that there are fewer recreational facilities and that more of the land is used for other functions such as offices, residences, and shops. However, as older adults mainly walk or cycle for recreation in China (Liu et al., 2020), if there is an insufficiency of recreational facilities, this may discourage them from doing so. Third, the connectivity of intersections was positively related to active travel. The connectivity of intersections is positively related to the walkability of the neighbourhood because it indicates that pedestrians can get from one place to another more easily when there are more intersections available to them (Bentley et al., 2018). Fourth, bus stop density was negatively related to the propensity for active travel, but the distance to the nearest metro

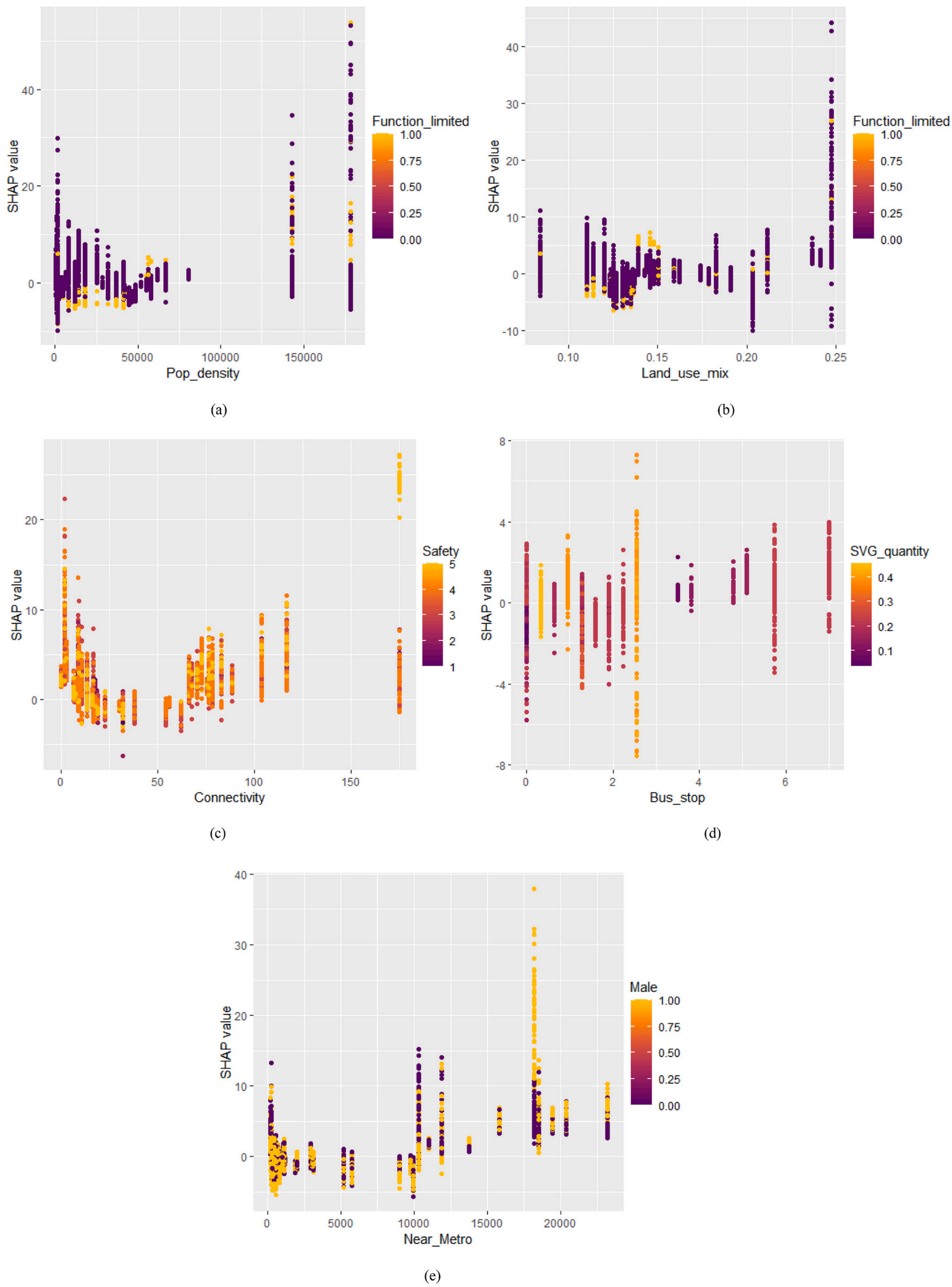

Fig. 4. Non-linear impacts of other built environment variables on the duration of active travel: (a) Neighbourhood population density; (b) Index of land use mix; (c) Connectivity of intersections; (d) Density of bus stops; (e) Distance to the nearest metro station.

station and bus stop density were positively related to the duration of active travel. This may be because, if there are good bus services within easy reach, they provide substitute modes of transport for walking or cycling (Piatkowski et al., 2015; Hasnine et al., 2018), so older adults tend to walk or cycle less in these neighbourhoods. However, the provision of better public transportation services also means there are likely to be fewer walking or cycling-related resources/facilities (e.g., pavements and cycle lanes), so journeys on foot or by bicycle may be less convenient and take longer (Piatkowski et al., 2015), which increases the duration of journeys made on foot or by bicycle.

6.2. Limitations

First, it should be noted that the machine learning approach may only reveal the mathematical association between SVG and active travel as the predictions made by mathematical tools do not always correspond in precisely to real-world contexts. Therefore, the findings of this study should be carefully interpreted and may not be directly valid for other locations. Second, our analysis was based on a cross-sectional survey, which means it may not be possible to infer any causality between street-level greenery and active travel among older adults. Hence, we were unable to fully disentangle the effects of residential self-selection (Cao et al., 2009). For instance, the choices made by the participants about their residential location, which are not visible, may affect the way that green space is arranged and their active travel behaviour; thus, the links we observed between these factors could have been distorted. Third, active travel was measured by answers to self-reported questions, which could have resulted in measurement bias as the respondents may not have remembered their previous active travel behaviour accurately. In addition, we did not have access to information about people's daily activities, so we were unable to identify the respondents' destinations or purpose of each active travel trip, which prevented us from better understanding the associations between green space and active travel. Fourth, street view data is also not without its limitations. For instance, the SAGE data was collected in 2010, while the SVG data was collected in 2013. Therefore, this kind of temporal mismatch between different data sources may lead to bias regarding the association between SVG and active travel among older adults. It should also be borne in mind that the street view data were downloaded within a certain period of time, which means they are unable to reflect seasonal variations in street-level greenery between summer and winter. It is also possible that street view data may be unavailable for some areas, such as private gardens, which may still be frequented by members of the ageing population. Fifth, we only measured street-level greenery within residential neighbourhoods and may have neglected to take other contextual factors, such as recreational facilities outside of the neighbourhood, that older adults may also use, into account. Last, we assessed the amount of street-level greenery using a circular buffer for each neighbourhood, and this could lead to the modifiable areal unit problem, which means that when any changes are made to the size or shape of the residential buffer, the effect size and significance level for the target association may also change (Fotheringham and Wong, 1991).

7. Policy and planning implications

The findings from this study have important implications for promoting active travel among the ageing population. First, SVG-quantity seemed to be more important than SVG-quality in predicting older adults' active travel behaviour, so more street-level vegetation such as trees should be provided around major streets, where the density of the ageing population is high. Second, because SVG-quantity was positively linked to the propensity for and duration of active travel, but the association was nonlinear, it is important to identify the optimal levels of SVG-quantity. For example, we found that the saturation point of SVG-quantity was about 0.25, so there should be approximately 25 % of visible vegetation, such as trees on the street, to maximise its benefits for active travellers. Third, SVG-quality was positively correlated to the propensity for active travel, but the association became inverse when SVG-quality exceeded a specific cut-off point. Therefore, the cut-off point should be identified for SVG-quality in different neighbourhoods to ensure that it does not discourage active travel in the ageing population. For instance, more public investment could be targeted at deprived neighbourhoods to improve their SVG-quality as they may be more influenced by, and have higher optimal levels of SVG-quality in the Chinese context (Wang et al., 2022). Last, we also found that the neighbourhood population density, index of land use mix, connectivity of interactions, and density of bus stops, had a nonlinear association with active travel, so attention needs to be paid to the optimal level of different built environment factors. For example, connectivity should be increased to a relatively higher level.

8. Conclusions

This research is among the first to investigate the nonlinear impacts of both the quality and quantity of street-level greenery on active travel among older adults in a major Chinese city. Our analysis suggested that the quantity of street-level greenery was relatively more important than the quality in terms of predicting active travel behaviour. The results also clearly demonstrated the nonlinear effects of street-level greenery on active travel among older adults. More specifically, SVG-quantity was positively linked to the propensity for and duration of active travel, but the association was nonlinear. However, SVG-quality was initially positively related to the propensity for active travel, but the association then became inverse when SVG-quality exceeded the cut-off point. SVG-quality was found to have a nonlinear and positive relationship with the duration of active travel. However, this study was based on a cross-sectional survey, which means it may not be possible to infer any causality. Therefore, future studies should use longitudinal data. These results confirmed the importance of considering nonlinear and heterogeneous relationships between the quantity and quality of street-level greenery and active travel among the ageing population. The findings have implications for policymakers which suggests that improving the provision of street-level greenery is crucial for facilitating more active lifestyles among the ageing population.

CRediT authorship contribution statement

Ruoyu Wang: Writing – original draft, Visualization, Software, Methodology, Data curation, Conceptualization, Formal analysis, Writing – review & editing. **Jiaying Zhang:** Investigation, Funding acquisition, Writing – review & editing. **Dongwei Liu:** Investigation, Funding acquisition, Writing – review & editing. **Yao Yao:** Validation, Resources, Investigation, Writing – review & editing. **Mengqiu Cao:** Writing – review & editing, Supervision, Resources.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jtrangeo.2025.104299.

Data availability

The data that has been used is confidential.

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