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The built environment's nonlinear effects on the elderly's propensity to walk

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The increased ageing of the population is a vital and upcoming challenge for China. Walking is one of the easiest and most common forms of exercise for older people, and promoting walking among older people is important for reducing medical stress. Streetscape green visibility and the normalised difference vegetation index (NDVI) are perceptible architectural elements, both of which promote walking behaviour. Methodologically we used Baidu Street View images and extracted NDVI from streetscape green visibility and remote sensing to scrutinize the nonlinear effects of streetscape green visibility and NDVI on older people's walking behaviour. The study adopted a random forest machine learning model. The findings indicate that the impact of streetscape green visibility on elderly walking is superior to NDVI, while both have a favourable influence on senior walking propensity within a particular range but a negative effect on elderly walking inside that range. Overall the built environment had a non-linear effect on the propensity to walk of older people. Therefore, this study allows the calculation of optimal thresholds for the physical environment, which can be used by governments and planners to formulate policies and select appropriate environmental thresholds as indicators to update or build a community walking environment that meets the needs of local older people, depending on their own economic situation.

KEYWORDS

green visibility, built environment, walking, random forest, older people

1. Introduction

According to the results of China's seventh national census compared to 2010, the population aged 60 and over rose by 5.44 percentage points (Statistics NBo, 2021). These figures indicate that the proportion of the population aged 60 and over is increasing and that more and more middle-aged people are entering old age with the expectation of a longer life expectancy. The ageing of the population is becoming a growing problem and there is an urgent need to increase the independence and self-care of older people, as otherwise, the burden on society and healthcare will continue to increase.

The World Health Organization recommends that older people get at least 150 min of appropriate physical activity per week; walking is the simplest form of low-intensity physical activity for humans, and increasing the amount of time older people spend walking is beneficial for improving their own health status (Nordbakke and Schwanen, 2014). Encouraging older people to be active in walking for travel is an important means of keeping them fit and ensuring a better quality of life (Moniruzzaman and Páez, 2016; Curl and Mason, 2019). Also walking is a common mode of travel. Walking can also help people access their destinations in some situations that are not accessible by cars and transit (Cheng et al., 2019; Chen et al., 2021; Yang et al., 2022a, 2023a,b). Walking can also increase older people's sense of well-being and happiness by maintaining their independence through social participation (Nordbakke and Schwanen, 2014).

Research has shown that urban greenery plays a positive role in the walking time and propensity of elders (Lu et al., 2018). Assessing urban greening has been an important topic, and in the past urban greening assessments have tended to be flat, site surveys, aerial photography and satellite remote sensing images. These data images are often presented as bird's eye views and top views; however, these methods are too traditional and are not perceived by the population, ignoring the perceptions of the people themselves (Kang et al., 2020). Image analysis of urban street scenes is rapidly developing rapidly in new research; street images have been rapidly developed in recent years in the field of public health care, with results indicating that street images are more easily perceived by the population and can provide a more objective image of the greenery of the street (Zang et al., 2020). However, in cases where there are missing data in the street view images, an objective and comprehensive assessment can be made together with the remote sensing images.

According to extant research on the effect of socioeconomic and demographic factors and built environment features on older adults' walking behavior, environmental factors such as density, land use mix, and street connectivity are the most significant. Relatively few studies have explored the effect of greening on older adults' walking behavior, and those that do exist have assumed a linear connection between walking behavior and other environmental parameters (Yang et al., 2019, 2022b; Zang et al., 2020). Nevertheless, it has been demonstrated that the link between the built environment and the walking behavior of older adults may also be nonlinear (Ding et al., 2019; Liu et al., 2021). Peer effects may be used to explain the link between nonlinearity and walking. The main focus in the most recent studies has been on nonlinearity, where the nonlinear association between the built environment and the walking behavior of older people is analyzed. Only one of these studies has been conducted on the nonlinearity of green views on walking behavior, however. With a proper understanding of the substantive implications of the nonlinear benefits, there is a need for a more in-depth study of the nonlinearity between the built environment and walking behavior.

To investigate the above issues in more depth, we used 597 valid data from our research group's March 2021 survey of older people aged 65 and above in Guangzhou using the International Physical Ability Questionnaire (IPAQ), Baidu Street View (BSV) images and 2021 NDVI images to assess older people's willingness to walk and the propensity to green their environment, respectively. A random forest model was used to evaluate the effect of urban greening and street greening on older people's willingness to walk, while a binary logistic regression model was used and compared with the random forest model.

The main research objectives of this paper are as follows:

1. To fill the gap in the study of non-linear comparison between streetscape green visibility and NDVI.
2. To examine the nonlinear and threshold impacts of urban and streetscape vegetation on walking behavior.
3. To investigate the nonlinear and threshold impacts of internal environmental characteristics (e.g., Density, Design, Diversity etc. "3Ds") on older adults' walking behavior.

2. Literature review

Numerous experts have conducted studies on the built environment's effect on older adults. A search of the relevant literature in the Web of Science to retrieve nearly 17 relevant articles from 2005 to 2022. The papers were first filtered by topic and then manually filtered by the relevance of the abstract content to this study. Table 1 summarizes the screened research on the association between the built environment and older adults' walking behavior. The table does not present sociodemographic characteristics, but rather primarily reflects the built environment as the subject of subjective versus objective measures and as the variable that has received the most research attention to date.

Certain characteristics of the built environment (e.g., population density, land street connectivity, etc.) generally have consistent impacts. However, the results from practice (e.g., the effect of pedestrian facilities on walking) need more investigation due to disparities in prediction, control variables and study techniques.

Most of the research methods are geographically weighted regression models and are dominated by traditional linear regression and binary logistic regression, which have limitations. In a recent paper, Cheng et al. used a random forest model for modelling (Cheng et al., 2020). Compared to traditional geographically weighted regression models, this model is more accurate in predicting and confirming that the built environment influences older people to walk in a nonlinear way, but more research is needed to validate and add to the theory.

In the regions studied, North American cities have received more academic attention than South American cities, probably because the economies of North America are more developed. The European cities studied have been mainly in Belgium and the Netherlands, where ageing is relatively high, and to a lesser extent in Australia, probably because ageing is less of an issue in Australia. Over the recent decade, Asian cities (e.g., Harbin, Hong Kong, Nanjing, Zhongshan, and Guangzhou) have progressively migrated into the primary research area. The majority of Asian research was completed after 2010. Consequently, as a characteristic of the built environment, Zang et al. (2020) and have only recently focused on streetscape greenery. This is largely due to advances in greenery measurement techniques that enable accurate and efficient estimation of perceived greenery at eye height, as well as the provision of street view image data that is available for free from the map website. Most notably, such nonlinear impacts of the built environment on older adults' walking behavior have received less attention. Additionally, Cheng et al. (2020) and Van Cauwenberg et al. (2011) conducted a comprehensive review of prior studies on the influence of the built environment on older adults' walking behavior.

Through the above literature review and in the context of the medical pressures of ageing that China is facing, it is important to identify the nonlinear effect of greening on the propensity of older people in China to walk for 10 min, which will help to verify whether the findings of previous studies are applicable in China and to fill in the research gap on the correlation between greening and the propensity to walk.

3. Data and method

3.1. Research program

This research is based on a random intercept around the community that was chosen to reflect the various population density zonings of Guangzhou City Planning zones in the surrounding community. Density zones 1, 2, and 3 correspond to low-, medium-, and high-density regions in this article. According to the March 2021 price sample, there are six groups: low socioeconomic status (SES), high SES, low SES, >30,000 RMB/m2 and high SES. Ages 65–74, 74–84, and 85 and above were considered. To eliminate seasonal impacts, respondents were questioned in the spring. The survey took into account sociodemographic variables (e.g., employment, age, and level of

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TABLE 1 Summary of studies on the built environment's effect on walking for older adults.

Reference	Context/ Walking behaviour measure(s)	Sample	Built environment measures	Modelling approach	Conclusion
Mendes de Leon et al. (2009)	Chicago, U. S./ Walking time	4,317 people aged ≥65	Disorder in the neighbourhood (e.g., litter, trash, vandalism, and broken sidewalks)	Multilevel linear regression model	The neighbourhood level was disordered (all $p > 0.10$) and was significantly associated with walking, independent of other correlates of neighbourhood perceptions and walking at the individual level ($\beta = -1.46$, $p = 0.08$). Further adjustment for ethnicity weakened this association to a marginally significant level. Neighbourhood conditions may influence older people's walking behaviour ($\beta = -2.35$, $p = 0.01$), particularly conditions reflecting physical neglect or social threat. Promoting walking behaviour in older people may require improvements in the safety and maintenance of the neighbourhood environment.
Procter-Gray et al. (2015)	Boston, U.S./ Transport walking time and recreational walking time	745 people aged ≥70	Access to the bus, hospital, etc.	Logistic regression model	Across the 16 communities in the study area, the prevalence of recreational walking was relatively uniform, while the prevalence of utilitarian walking varied. Both types of walking were associated with personal health and physical ability (AREA = 0.56, $p < 0.001$). However, utilitarian walking was also strongly associated with community socio-economic status and several measures of access to amenities, whereas recreational walking was not. Utilitarian walking is strongly influenced by the community environment, but intrinsic factors may be more important for recreational walking.
Shigematsu et al. (2009)	King County/ Seattle, U.S./ Transport walking propensity and recreational walking propensity	360 people aged ≥66	Population density, street connectivity, etc.	Partial correlation analysis	Walking for transportation was significantly associated with a wide range of perceived neighbourhood attributes in all age groups, but not walking for recreation. In the youngest age group, walking for transport was significantly related to almost all neighbourhood environmental variables. In contrast, in the two oldest groups, only two environmental attributes, proximity to non-residential uses (e.g., shops) and recreational facilities, were moderately associated with walking for transport. The availability of non-residential destinations and recreational facilities within walking distance may be among the most important attributes supporting physical activity among older people.
Maisel (2016)	New York, U.S./ Walking time	121 people aged ≥65	Population density, land use mix, street connection, and so forth.	Spearman rank correlation analysis	Perceptions of street connectivity, crime and traffic safety, and overall satisfaction were associated with specific types of walking behaviour, and the strength of this relationship varied by community type. Sociodemographic variables, such as age and gender, were associated with certain types and amounts of walking behaviour among older people, including in each community type. The importance of perceived street connectivity, regardless of community type, and the impact of perceived crime safety in rural communities on older people's walking behaviour.
Barnes et al. (2016)	British Columbia, Canada/Transport walking propensity	3,860 people aged ≥45	Access to public transportation and walkability	Logistic regression model	The 34% increase in odds of walking to travel (OR = 1.34; 95% CI: 1.23, 1.47) and the 28% increase in odds of using public transport (OR = 1.28; 95% CI: 1.17, 1.40) were associated. People in communities with excellent transit/passenger haven were more than three and a half times more likely to walk to transit and three and a half times more likely to use public transportation compared to communities with minimal transit/partial transit ($p < 0.005$). Stronger associations were observed between transit scores and active transportation in the older population and between walking scores and transit walking in the non-retired population.
Moniruzzaman and Páez (2016)	Montreal, Canada/ Walking propensity	31,631 one-way home-based trips made by people aged ≥55	Population density, employment density, etc.	Logistic regression model	Twenty-nine items were tabulated and tested. 13 items negated the original assumption of independence at $p < 0.05$. These locations were then targeted for walkability audits. A walkability audit of 403 streets was used to demonstrate this concept. The items audited were summarised in a contingency table and independent chi-square tests were used to identify streetscape elements associated with pedestrian traffic.
Neves et al. (2021)	São Paulo, Brazil/ Walking options	12,000 people aged ≥60 years	Population density, origins, and accessibility to destinations, etc.	Logistic regression model	Applying a traditional logit model, the results are that for the city of São Paulo, the built environment variable is more relevant to the place of departure $p < 0.05$, and the dimension most relevant to the choice of walking is diversity, probably due to socio-economic reasons. Individual characteristics also had a significant effect, along with age, gender and income, which must be taken into account when developing local public policy to encourage walking.

(Continued)

TABLE 1 (Continued)

Reference	Context/ Walking behaviour measure(s)	Sample	Built environment measures	Modelling approach	Conclusion
Etman et al. (2014)	Spijkenisse, Rotterdam, the Netherlands/ Walking time	408 people aged ≥65	Access to functional characteristics, aesthetics, and destination accessibility, etc.	Linear regression model	Increases in infrastructure (e.g., presence of pavements and benches) in the 400 m buffer, urban tidiness (e.g., absence of litter and graffiti) in the 800 and 1,200 m buffers, and an additional destination in the 400 and 800 m buffers were associated with more transit-oriented walking (CI 1.07–7.32; $p < 0.05$). No differences were found between frail and non-frail older people.
Van Holle et al. (2016)	Ghent, Belgium/ Transport walking time	438 people aged ≥65	Land use mix, street connection, and walkability, etc.	Multilevel linear regression model	Neighbourhood walkability did not moderate the association between physical function and MVPA. In low-income neighbourhoods, the relationship between physical functioning and MVPA was not moderated ($p = 0.769$); there was a strong overall positive association between physical functioning and accelerometer-based MVPA ($p < 0.001$), and only in high-income, high-walking neighbourhoods were higher physical functioning scores associated with higher levels of MVPA ($p < 0.001$).
Böcker et al. (2017)	Greater Rotterdam, the Netherlands/ Walking propensity	147 people aged ≥65	Diversification of buildings, coverage of green space, etc.	Logistic regression model	The transport needs of older people are crucial. Recognise the mobility needs of older people. As older people increasingly As older people increasingly use cars, encourage older people to use more physically active and environmentally friendly modes of transport, such as cycling. Due to the increasing use of cars by older people.
Nguyen and Mertens (2021)	Belgium/Transport walking time	503 people aged ≥65	Park density, public transport density, intersection density, etc.	Negative binomial regression model	Older people living in environments with higher residential density, higher park density, lower public transport density and higher entropy index have higher levels of active transport ($p = 0.046$). In addition, the different types of neighbourhoods in which older people live lead to different moderating factors that play a decisive role in increasing active transport behaviour among older people ($p = 0.015$).
Boruff et al. (2012)	Perth, Australia/ Walking trip frequency	325 people living in 32 retirement villages	Land-use exposure	Logistic regression model	Differences in built environment characteristics were found within the newly created 'neighbourhoods' ($p = 0.024$). Exposure measures derived from alternative buffering techniques provided a better fit when examining the relationship between land use and walking for transit or recreation ($p = 0.024$). The size and orientation of buffers influenced the relationship between built environment measures and recreational walking for older people ($p = 0.066$).
Ghani et al. (2018)	Brisbane, Australia/ Transport walking duration	11,035 people aged 58 to 65	Population density, connection of streets, etc.	Multilevel binary logistic regression model	A relatively limited role was played in terms of neighbourhood differences in the relationship between age and walking. Residential density and street connectivity explained 13 and 9% of the inter-neighbourhood variation in WfT for each age group, respectively. Older people were more sensitive to their neighbourhood environment. Age differences in WfT were smaller in areas with higher residential density and street connectivity.
Cheng et al. (2020)	Nanjing, China/ Walking time	702 people aged ≥60	Population density, land use mix, street connectivity, the total number of bus stations, the total number of bike-sharing stations, the distance to the closest square/park, the distance to the closest card/chess room.	Random Forest Model	All the built environment attributes analysed tend to have prominent non-linear and threshold effects on walking times. The combination of population density and land use can only increase walking by older people to a certain extent. Areas with too high a population density and an excessive mix of land uses can even lead to a reduction in walking. Thus, interventions in the built environment are only effective up to a certain point.

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TABLE 1 (Continued)

Reference	Context/ Walking behaviour measure(s)	Sample	Built environment measures	Modelling approach	Conclusion
Yang et al. (2021)	Hong Kong, China/Walking propensity	101,385 people aged ≥60	Population density, land use mix, intersection density, the proximity of bus stations, availability of recreational amenities greenery in public spaces.	Random Forest Model	Streetscape greenery has the second highest relative importance (12.82%), surpassed only by age (16.65%). Streetscape greenery has a positive effect on propensity to walk within a certain range, but outside of that range the positive association no longer holds. Non-linear associations were also investigated for other built environment attributes.
Cheng et al. (2021)	Nanjing, China/ Walking time	702 people aged ≥60	Population density, land use mix, connection of streets the quantity of bus stations, the number of stations for bike sharing, the distance to the closest square/ park, the distance to the closest card/ chess room	Global Moran's I test model	There is spatial heterogeneity in built environment effects across the study area. It affects all relationships, with subtle differences in significance levels, parameter sizes or sign reversals, depending on location. As a result, policy interventions will only be effective in certain areas for certain built environment attributes. Spatial heterogeneity stems from contextual effects, i.e., the specificity of places with a discriminatory composition of individual and/or environmental characteristics.
Wu et al. (2021)	Zhong shan, China/Walking frequency	4,784 people aged ≥60	Population density, residential density, density of sidewalks, density of road network, density of bus stations, accessibility for commercial purposes, distance from the centre, mixture, greenspace.	The Semiparametric GAMM as penalized generalised linear models	Non-linear relationships exist for five of the six built environment characteristics. Within certain thresholds, population density, pavement density, bus stop density, land use mix and percentage of green space were positively correlated with walking trips by older people. In addition, land use mix and percentage of green space showed an inverse 'V' shaped relationship. Built environment features can support or hinder the frequency of walking by older people. This is a good guide to cost effectiveness.
Zang et al. (2021)	Guang zhou China/Walking time	597 people aged ≥60	population density, land use mix, street connection.	Global Moran's I test model	Land use mix and NDVI were positively correlated with traffic walking in low density areas, and traffic walking was negatively correlated with road intermediary centrality (BtE) and point of interest (PoI) density. In addition, recreational walking in medium density areas was negatively correlated with self-rated health, road intersection density and PoI density. Street connectivity, road intersection density, DNVI and recreational walking in high density areas showed negative correlations.

education) as well as travel information (e.g., frequency of walking trips, broad questions related to walking time). We pooled the collected data of 600 older adults to increase the sample size, and after eliminating incomplete data records, we obtained a random group of 597 older adults in Guangzhou (see Figure 1).

The preliminary analysis of the 12 sample regions revealed considerable disparities in the built environment between low and high socioeconomic status districts in Guangzhou. To achieve appropriate impartiality and to avoid the model that ignores specific environmental factors from the computations, we simulated and computed the low- and high-SES regions evenly. The chosen sample locations are summarized in Figure 1.

The International Physical Activity Questionnaire-Long Version (IPAQ-LC) was used to categorize respondents' desire to walk in the questionnaire according to the purpose of the interview. All respondents were divided into two groups: those who had some willingness to walk within 24 h (whether walking = 1) and those who did not (whether walking = 0), with the willingness to walk per person as the predictor variable. Additionally, areas beyond the residential context (greater than 1,000 m) were omitted.

3.2. Streetscape greenery and NDVI

The static 360° street-view picture covers a larger geographic area, has fewer data mistakes, is more cost- and time-efficient, and is sampled by humans more than standard data sources (Kang et al., 2020). In comparison to Google Street-view (GSV), Baidu Street-view (BSV) is more China-centric, with picture data spanning all major cities in the country and gathered by sensor automobiles equipped with GPS devices assuring both accuracy and timeliness.

Using BSV images, a streetscape greenery index with a highly similar perspective to the human eye was obtained, which reflects the degree of greenery directly acquired by the human eye. The method is as follows. First, the coordinates are geocoded into ArcGIS software based on the subdivisions of the sampled elderly sample areas. A 1,000 m buffer zone is drawn based on the boundaries of the sample, and all primary to tertiary streets within the 1,000 m range are sampled and recorded, after which a fixed 50 m spacing is taken to generate sampling points in all streets within the buffer zone. A total of 40,000 BSV images are downloaded from the Baidu Maps developer platform for static map API download. For each location point, four images were sampled at 90, 180, 270, and 360° each to represent the 360° panorama image (Long et al., 2015; Zang et al., 2020; see Figure 2). The BSV-generated streetscape greening was calculated as follows:

$$Green\ view\ index = \frac{\sum_{i=1}^{4} Greenery\ pixels_i}{\sum_{i=1}^{4} Total\ pixels_i}$$

The NDVI normalized difference vegetation index (Tucker, 1979) can be used as a complement to green plant visibility where streetscape map coverage is incomplete to represent the chlorophyll content of the area in which it is located (Helbich, 2019). In secondary and tertiary roads relatively far from the main urban area, streetscape data are missing; in green sight assessment, NDVI, although not the most direct reflection of human vision to the same extent as streetscape, is the best data supplement in the absence of data. To provide a more objective assessment of the environment in the sample area, we used a map of Guangzhou city with an accuracy of 10 m extracted from remote sensing in August 2021 as a base map and calculated the pigment absorption of chlorophyll in the red band and the high reflection of vegetation in the near-infrared (NIR) band (see Figure 3). The formula for calculating NDVI is as follows:

$$NDVI = \frac{(NIR - R)}{(NIR + R)}$$

3.3. Variables

The prediction variables used were two minimal sociodemographic characteristics and nine variables relating to the built environment, with the exception of the streetscape and greenery variables, where we focused on seven environmental variables developed under the '3D' built environment assessment framework (Zang et al., 2019). All environmental variables were measured within ArcGIS software using geographic data from the national geographic information service platform SkyMap.[1]

Table 2 presents descriptive statistics for the predictor and predictive variables, from which it can be seen that 75% of the older adults did at least some walking in the 24-h period. The other 25% of older people did not walk.

3.4. Methodology

Random forests (a.k.a., random decision forests) are currently one of the most popular and effective computer learning algorithms in international competitions (Sagi and Rokach, 2020) and can perform data mining, classification and regression tasks and explain finer correlations between variables. This excellent machine learning algorithm was first proposed in 1995 by Tin (1995), and the "Stochastic Decision Forest" (Tin, 1998) constructed a forest comprised of several decision trees for classification and regression.

The random forest approach shown in Figure 4 combines the ease of a decision tree with the restriction to a subset of the sample's test and predictor variables. Random forests algorithmically reduce the variance and coordinate multiple decision trees together to optimize the model (Breiman, 2001), thus solving the overfitting challenge. The objective is to minimize the loss function and verify the accuracy of the findings by iteratively assessing the test and prediction sets using their own method until the loss function achieves a minimal value or stays stable. The random forest is made up of an infinite number of decision trees and works, as shown in Figure 4. To ensure the variety of the decision trees, two randomness tree treatments are applied. First, the training data are structured in such a way that each tree develops with a unique subsample. Second, features are randomly chosen to produce distinct groups of explanatory variables from which to divide the tree's nodes. Splitting continues in a single decision tree until the maximum tree depth is achieved. Based on the average answer of each location, a

1 https://www.tianditu.gov.cn/

single forecast is created. By averaging the predictions of all individual decision trees, the ultimate result is achieved.

Three factors significantly affect the forecasting effectiveness of random forest algorithms (Cheng et al., 2019); first, improving the accuracy of individual trees and second, reducing the similarity of each tree. Finally, we need to parameterize the whole model, most notably three parameters (Claesen and Moor, 2015): the tree's greatest depth, its total number of trees, and the number of splits. Random forest parameters are manually and continually checked to determine the optimal values. Most other machine learning approaches, including random forests, do not yield t statistics, p values, or other markers of statistical significance. However, the random forest can calculate the relative importance of variables and then visualize it with the following formula for the importance of variable x.

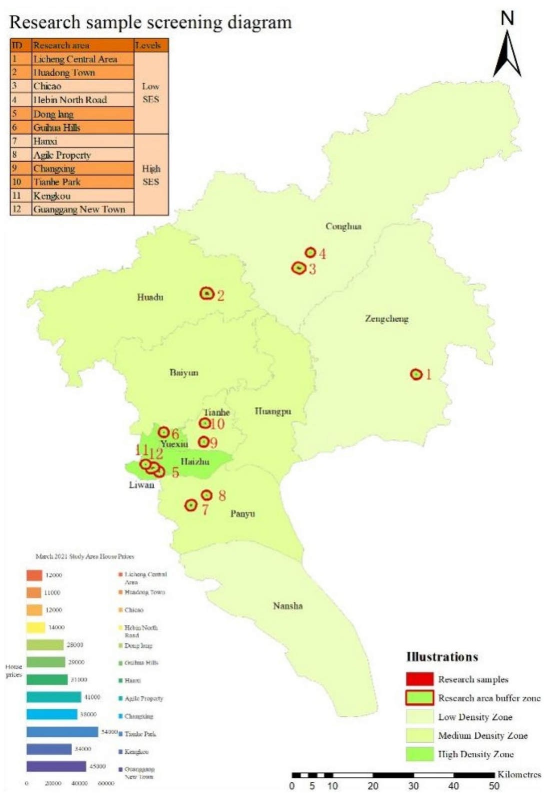

FIGURE 1
Research sample screening diagram.

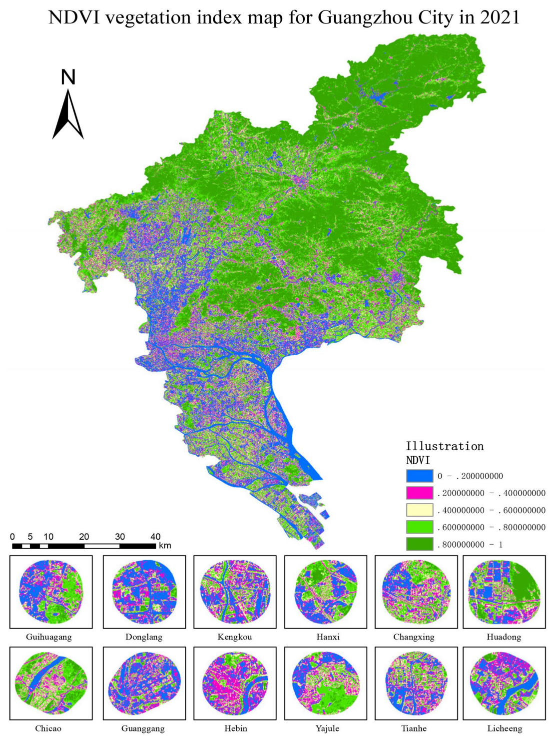

FIGURE 3
NDVI normalized difference vegetation index (NDVI) map for Guangzhou in 2021.

FIGURE 2
A random forest technique example.

TABLE 2 Summary statistics and descriptions of the predicted and predictor factors.

Variable	Description	Mean/Percentage	Std. Dev.
Predicted variable			
Walking propensity	Indicator variable = 1 if you walked on the reference day; = 0 otherwise.	0.75	0.43
Predictor variables: sociodemographics			
Age	Older people aged 65–74 (0: No; 1: Yes)	0.87	0.34
	Older people aged 74–84 (0: No; 1: Yes)	0.12	0.32
	Older people aged >85(0: No; 1: Yes)	0.02	0.12
Education level	Higher-educated respondents (0: No; 1: Yes)	0.13	0.34
	Secondary education respondents (0: No; 1: Yes)	0.77	0.42
	Less-educated respondents (0: No; 1: Yes)	0.1	0.30
Predictor variables: built environment			
Population density	Within the neighbourhood, population density is measured in terms of 100 persons per km^2.	1.24	1.04
Land-use density	Entropy for local land uses $H = -\left[\sum_{I=1}^{N} P_I * \ln(P_I)\right] / \ln(N)$, where pi represents the percentage of the i -th land use and N represents the total number of land use categories. Three land uses are studied in this research (N = 7): residential, office, commercial, medical, entertainment, public services, and education.	0.46	0.17
Street connectivity	Total sidewalk length/Total built-up area in a buffer zone (km/km^2)	1.74	0.18
Road intersection density	Within a density community at a street intersection (Unit: 1 km^2)	106.33	52.00
Number of bus stations	The total number of bus stations inside a 1Km buffer zone.	20.07	13.55
Bus stop distance	The shortest distance from the sample plot to the bus stop	229.56	186.404
NDVI	Difference between the NIR and red areas in terms of reflectance/Sum of the NIR and red regions in terms of reflection.	0.41	0.08
Streetscape green visibility	The green view index is determined by dividing the total number of pixels by the fraction of greenery pixels.	0.20	0.06
Sample size	597		

$$VI_{xi} = \frac{1}{N} \sum_{t} \left(OOB_{MSE}^{t} - OOB_{MSE,perm_i}^{t} \right)$$

where VI_{xi} is the importance of the variable, the total number of decision trees in a random forest model is denoted by N , OOB_{MSE}^{t} denotes the mean squared error t before the variables are ranked in the decision tree, and t , $OOB_{MSE,perm_i}^{t}$ denotes the mean squared error x_i after the variables are ranked (Breiman, 2001).

In contrast to standard regression-based statistical studies, which predetermine the (often linear) connections between predictor and predictor variables, random forest does not make these assumptions. Additionally, depending on the degree of the predictor variable, hypothetical random forest modelling generates partial dependency plots (PDPs) to illustrate the link between the test and predictor factors (Pedregosa et al., 2011). The equation for partial dependence is as follows:

$$\hat{f}_s(x_s) = \frac{1}{N} \sum_{i=1}^{N} \hat{f}(x_s, x_{ic})$$

where x_{ic} is the x_c value of the variable for the modelled dataset and N denotes the number of occurrences. The graph demonstrates how the built environment's influence on walking time is constant over a variety of nonlinear connections (Buitinck et al., 2013).

Prior to modelling, the independent variables were first checked for multicollinearity analysis, with all sociodemographic and environmental variables satisfying VIF < 5, ensuring that all variables were free of multicollinearity. For the purpose of random forest model pair optimization, a range of these three parameters was first determined (maximum tree depth is between 1 and 20, the number of features per tree is between 2 and 6, and between 10 and 1,000, and there is one interval per 10 trees). Second, we estimated a total of 8,000 (=20 × 4 × 100) potential combinations and used Area Under Curve (AUC) to evaluate model performance (Lee, 2019). After 900,000 tests, we discovered that the model stopped developing quarterly at a maximum tree depth of 8, a feature count of 4, and a tree count of 830, even though the root mean square deviation values were low and the model functioned well. Finally, the model was applied for further analysis.

3.5. Comparative analysis of random forest and binary logistic modelling

We evaluated the performance of random forest and binary logic modelling using tenfold cross-validation. Three common

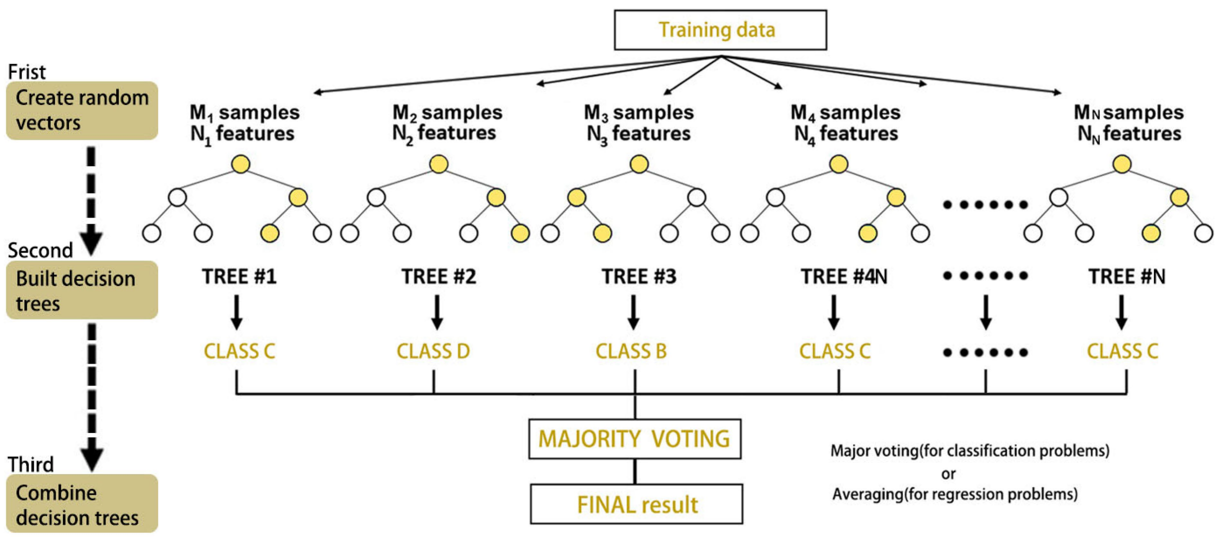

FIGURE 4
Depiction of the BSV-based method for estimating streetscape greenery at eye level.

classification metrics were used, namely, model accuracy, mean squared error and mean squared error. These three metrics were calculated as follows:

$$Accuracy = \frac{\sum_{i=1}^{N} TP_i + TN_i}{\sum_{i=1}^{N} TP_i + FN_i + FP_i + FPN_i}$$

$$MAE = \frac{1}{N}\sum_{I=1}^{N}\left(\hat{y}_i - y_i\right)^2$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_i - y_i\right)^2}$$

where Accuracy denotes the ratio of properly predicted samples to total predicted samples, N is the number of samples in the validation set, TPi denotes the number of correctly predicted samples (predicted walking tendency is True and actual walking tendency is also True), TNi is interpreted as (predicted walking tendency is False and actual walking tendency is also False), FPi is interpreted as (predicted walking tendency is True but predicted walking tendency is False), and FNi is interpreted as (predicted walking tendency is True 1 but actual walking tendency is Ture).

In the MAE and RMSE equations, N denotes the total number of respondents in the validation set, yi denotes the sample's projected propensity to walk, and y_i is the sample's actual propensity to walk; the lower the values of these two equations are, the more evidence of a more accurate model. The results of 10 cross-validations of the two models are shown in Table 3. All three metrics demonstrate that the random forest model beats the classic binary logistic regression equation and is more adaptable in its nonlinear performance (Zang et al., 2022).

TABLE 3 Comparison of random forest versus binary logistic regression results.

Model	Accuracy	MAE	RMSE
Random forest	0.67	0.23	0.41
Model logistico-binary	0.60	0.37	0.44

4. Result

4.1. Predictor variables' relative relevance

The relative relevance of the predictor factors is shown in Table 4, and their ordering is shown in Figure 5. The other '3DS' environmental factors are similarly extremely highly placed in the top five in terms of overall relative significance, ranging from (9.80–12.65%); it is worth noting that NDVI is ranked relatively low at number seven, with a value of (8.83%), suggesting that streetscape greenery has more influence on the propensity to walk than NDVI.

Environmental variables accounted for 82.92% of the total importance, while sociodemographic variables accounted for only 17.08%. This indicates that built environment characteristics significantly influence older persons' proclivity to walk, which is consistent with the results of Cheng et al. (2020) and Yang et al. (2021), who also studied the relationship between older adults and walking in Nanjing, China and Hong Kong, China, where built environment factors dominated in a nonlinear model. This result also complements the findings in the European and North American samples, where built environment variables had a greater impact on walking than sociodemographic variables (Gim, 2013; Wang and Ozbilen, 2020; Yu et al., 2021).

4.2. Nonlinear effect of streetscape green visibility and NDVI

As illustrated visually in Figures 6A,B, the random forest results for the predictor variables used to calculate PDPs illustrate the nonlinear

TABLE 4 The random forest algorithm calculates the relative relevance of predictor variables.

Variable category	Variable	Rank	Relative importance (%)	Total (%)
Sociodemographics				17.08
	Age	10	6.51	
	Education level	4	10.57	
Built environment				82.92
	Population density	5	9.80	
	Land-use density	2	12.65	
	Street connectivity	8	8.23	
	Road intersection density	3	10.70	
	Number of bus stations	6	8.97	
	Bus stop distance	9	7.99	
	NDVI	7	8.83	
	Streetscape green visibility	1	15.74	
Total relative importance				100

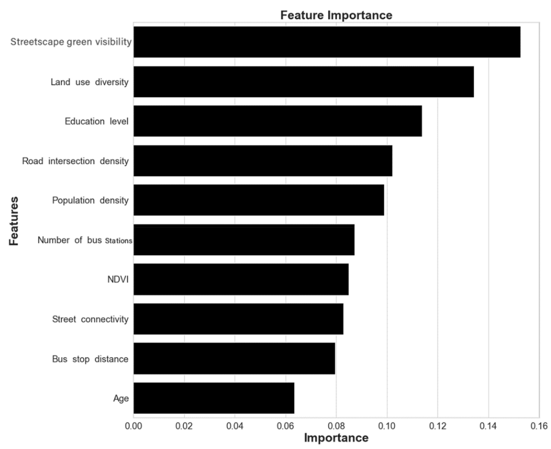

FIGURE 5
Predictor variables' relative relevance.

relationship between streetscape greenness and propensity to walk, where the x-axis represents the distribution of the predictor variables, the y-axis represents propensity to walk, the black line represents the predicted outcome, and the red line represents the smoothed curve of the predicted outcome. The smoothed curve may be used to more intuitively represent the trend of the expected outcomes (Tao et al., 2020).

The impact of streetscape green visibility on older adults' proclivity to walk is seen in Figure 6A. As the first environmental factor to influence the propensity to walk, its predictive index peaks at less than 0.24 and is positively correlated with the propensity to walk, with a decreasing trend line when green visibility exceeds 0.24, a finding consistent with related research findings (Yang et al., 2021). The impact of the streetscape green visibility is relatively limited, and when it reaches 0.24, a further increase in the streetscape green visibility does not increase the propensity of older people to walk.

Figure 6B shows the effect of NDVI on the propensity to walk of older people, peaking at an NDVI of 0.45, which is positively correlated with propensity to walk when the predicted index is less than 0.45 and negatively correlated with propensity to walk when the predicted index is above 0.45. One interpretation is that vegetation cover is already high when the NDVI is 0.45, and when the vegetation index increases further, its walkability visibility and environmental confinement also increase, and walkability decreases. Although the NDVI is not as important as the streetscape green visibility, it is a good guide to the propensity to walk.

4.3. Nonlinear effects of other built-environment variables

Figures 6C–H represent PDPs for other built environment variables. 5c shows a negative correlation between the population density predictive index and propensity to walk at less than 3.6, with population density having a negative effect on the propensity to walk, possibly indicating that more developed places with higher population density in the sample area are becoming less attractive to older people. This result is not very consistent with existing studies (Cheng et al., 2020; Yang et al., 2021). The shaky curve decreases faster when the walking index is 2, which may be due to older people disliking densely populated areas and preferring to walk in sparsely populated, quiet places.

The impact of land use mix on the inclination to walk is seen in Figure 6D, with a positive effect when the projected index of land use mix is smaller than 0.45, a result that is consistent with some of the literature results (Cerin et al., 2017; Cheng et al., 2020; Yang et al., 2021), where an appropriate land use mix of 0.45 provides a richer functional need and a stimulus for walking. A predictive index greater than 0.45 is negatively correlated with the propensity to walk, i.e., a high land use mix does not create a positive environment for walking.

Figures 6E,F show the nonlinear effects of road intersection density as well as street connectivity on the propensity to walk. Figure 6E predicts a positive correlation with the propensity to walk from 0 km–200 km, consistent with existing studies (Cheng et al., 2020). 在 For the time being no adverse effects on walking were found within the study area, which may be related to the urban infrastructure development. The sample area does not have a higher

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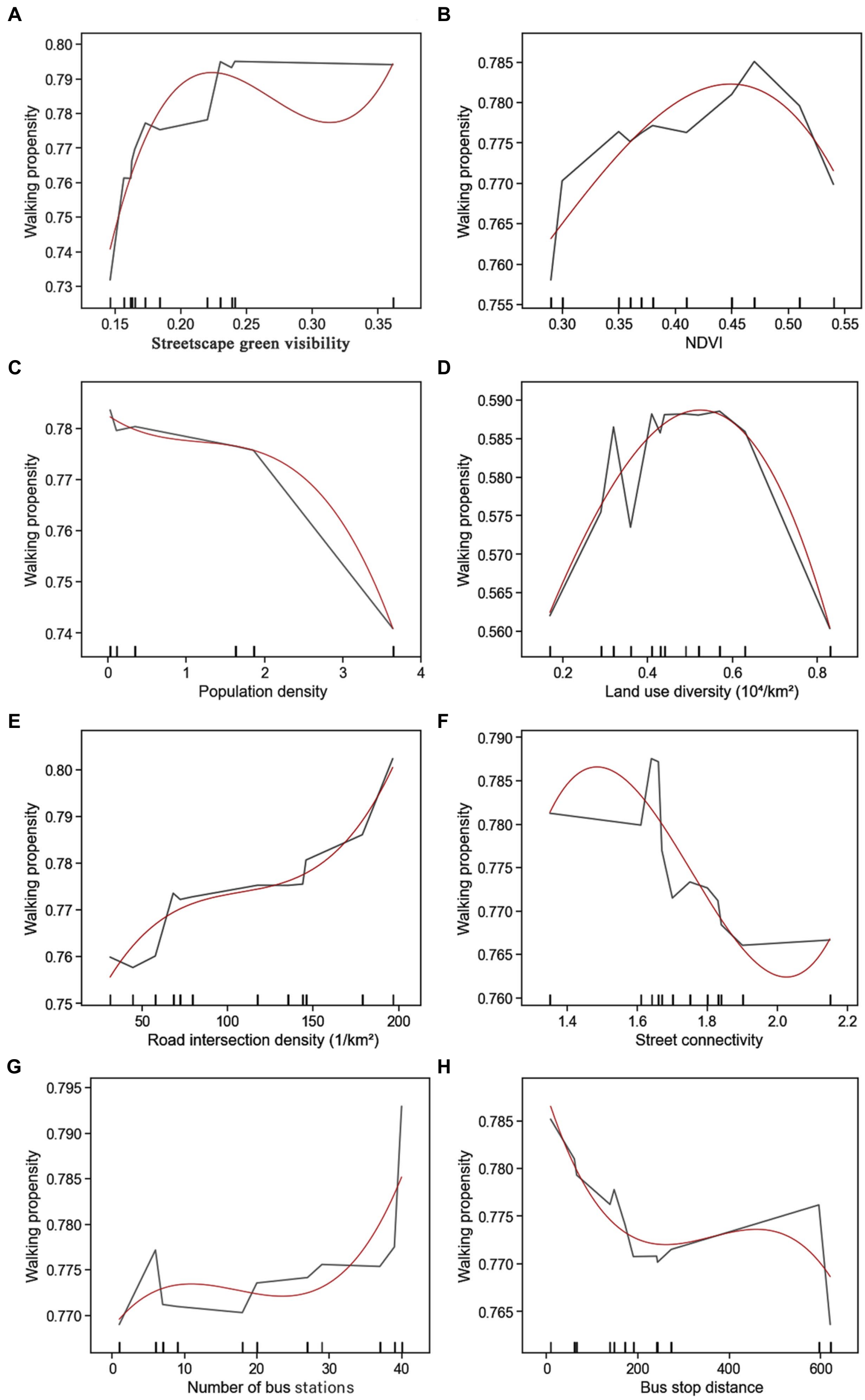

FIGURE 6
(A–H) The nonlinear effect of built-environment characteristics on walking proclivity.

denser road network to predict the effect of higher density road intersections on the propensity to walk, and it is not possible to confirm the research theory of Yang et al. (2021). The nonlinear effect of Figure 6F is more apparent when the predicted value of street connectivity is less than 0.15 and is positively correlated with propensity to walk and negatively correlated with propensity to walk in the range of 0.15–2.0. This may be because when connectivity is too high, it means that road junctions become complex and the elderly are less safe crossing the road, resulting in less walkability. Thus, while contemplating the addition of more road junctions, it is

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critical to examine the complexity of the intersections to create a more pleasant walking environment.

The nonlinear impacts of the number of bus stations and the shortest distance to the bus stop are shown in Figures 6G,H, as predicted from both the findings and Cheng and Yang's research. All of the projected outcomes are positively associated with a proclivity to walk.

5. Discussion and conclusion

In the context of China's growing ageing problem, it is important to build more walkable community environments. Walking allows older people to maintain their health status better, and it is necessary to promote walking frequency among older people through the environment. This study uses machine learning to calculate streetscape greenness and greenness indices through non-linear modelling to fill a gap in the non-linear influence of the Normalized Vegetation Variance Index (NDVI) on propensity to walk, complementing observations of the threshold influence of streetscape vegetation and internal features of the built environment on the propensity to walk of older people. Such comparisons have rarely been studied in the non-linear modelling literature. As a result (Statistics NBo, 2021), Streetscape Green Visibility is more perceived by older people than NDVI, and Streetscape Green Visibility is the most important (Nordbakke and Schwanen, 2014). Both Streetscape Green Visibility and NDVI have a nonlinear effect on walking propensity (Curl and Mason, 2019). When the predictive index of Green Streetscape Visibility is less than 0.24, it is favorably connected with walking propensity; however, when the predictive index is greater than 0.24, it has a negligible influence on walking propensity (Moniruzzaman and Páez, 2016). The built environment, such as 3Ds, also showed an effect on walking propensity in the nonlinear model.

In practice, it is more difficult to control the NDVI to a value of 0.45, as it is more macroscopic than the street-level green vision, whereas it is relatively easy to control the streetscape green visibility, with green pixels occupying 1/4 of the human eye's visual range to maximize the propensity for older people to walk. While it is important to use the NDVI as a criterion for assessment, it is also important to assess the streetscape greenness and walkability of a community from the perspective of the people themselves by taking photographs of the actual environment in a sample of the planned area. This will enable poorer neighborhoods to be optimized and avoid the unnecessary waste of human and material resources by overinvesting in greenery in existing good environments.

This research adopts a more scientific approach and relevance, and its findings will provide a scientific basis for policy-makers. Researchers can quantify the space, and previous research illustrates the existence of nonlinear effects of the built environment on human behavior. Research should focus on both linear research and nonlinear research. The use of machine learning helps researchers construct more complex models of the link between the built environment and behavior and to dig deeper into the results and conclusions. Additionally, this study is also a practice of a new approach, as the traditional linear system can only prove the link between two variables, but it is not easy to reflect the true complexity of the impact of the environment on the walking behavior of older adults. This study uses a nonlinear model to provide an optimal index of the physical environment, which avoids wasting resources. The Government can use these environmental thresholds to develop policies to regulate the use of green infrastructure, especially in less economically developed cities where the environmental thresholds have been shown to be lower than in developed cities, and should choose the appropriate environmental thresholds as indicators to update or build a community walking environment that meets the needs of the local elderly according to their own economic situation. The construction of a nature-centric green city is currently a significant trend in international urban planning, but due to the limitations of each city's position and its own economic development more research is urgently needed to help different cities tailor their own green-friendly city standards to maximize the efficiency of economic resource use, and this study provides a green construction indicator solution for other scholars to consider.

This study provides relatively new findings and proof of previous theories, offering new vivid ideas for future research. However, there are still limitations. First, Guangzhou is a first-tier city in China, a city with a relatively high mix of population and land use, and similar studies are currently available in Nanjing and Hong Kong; however, the nonlinear effects of the built environment on older people's propensity to walk need to be studied in more regions to confirm the applicability of the generalizations and transferability of the findings. Second, the built environment (streetscape green views and NDVI) has a good synergistic effect on promoting walking propensity. Third, as a data-driven approach, the random forest method used in this study relies on the relative importance of orthogonal decision edges and predictor variables, which may not find optimal partitioning. Therefore, the choice of independent variables should be reversed in that all factors of the dependent variable cannot be controlled for in the decision tree; therefore, the results are still biased. Fourth, in the actual walk, the elderly are experiencing a richer experience through the greenery, based on the streetscape green visibility not capturing all the perceptions of the elderly, with the development of science and technology and the relative maturity of the Unreal 5 engine, a relatively realistic scenario can be built and combined with wearable devices to assess the environmental conditions more deeply. Fifth, the study's nonlinearity and threshold effects provide critical insights for land use and transportation strategies aimed at encouraging older adults to walk.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Ethical approval was not required for the study involving human participants in accordance with the local legislation and institutional requirements.

Author contributions

PZ: conceptualization. HZ and FX: resources. KC and JM: supervision. HQ and YQ: validation. PZ and HQ: writing—original draft. KL and HG: writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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