Linear or nonlinear- Research on street walkability factor threshold based on regression and random forest algorithm comparison (16p times new roman)

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Abstract: Each paper should be preceded by an abstract (10–15 lines long) that summarises the content. How to improve the walkability of urban streets has become one of the hot topics in the field of urban design. The evaluation system and methods of the walkability of the urban built environment in Europe, America and Australia have been relatively perfect, and relevant research is also being carried out in our country, with a considerable number of studies. However, in terms of practical needs, there are still relatively few studies on how to accurately and effectively determine the threshold of street environment factors. The commonly used regression algorithms based on linear assumption not only have high requirements on the original data distribution, sample size, and the independence of independent variables, but also often lose some key variable data that do not meet the data distribution assumption or cause collinearity when constructing mathematical statistical models to ensure the fitting effect of the model. With the continuous development of new algorithms such as Random Forest based on machine learning, computers can train and learn data through design and analysis, so as to generate multiple prediction models to cope with a variety of nonlinear and complex relationships. The results of multi-model fitting can further generate PDP (Partial dependence plots) to visually show the influence and trend of built environment elements on environmental behavior at different numerical levels, which greatly improves the completeness and accuracy of indicator threshold judgment. Based on the performance comparison of regression model and random forest model, this paper explores the difference of threshold determination results between the two algorithms in the built environment and walking behavior data of 1,055 street segments in the central urban area of Shanghai. It is found that the nonlinear algorithm has significant advantages in variable loss, model fitting degree, weight ranking, and threshold visualization. It is expected to provide theoretical basis and technical support for the guidance and control of street walkability design in our country in the refined era. (10p times new roman)

Keywords: Nonlinear algorithm; Regression; Random forest; Streets; walkability (10p times new roman)

1 Background ("H1") (12p times new roman)

In light of these benefits, environmental planners and policymakers are eager to identify built environmental factors that promote outdoor walking for older adults. However, current planning approaches often lack a gerontological focus (e.g., Handy et al., 2002; Lee et al., 2009; Ross and Searle, 2019; Stappers et al., 2021). A more deliberate emphasis on the needs of older adults has the potential to influence walking duration and frequency while creating opportunities for enrichment (Cunningham et al., 2004; King et al., 2005; Berke et al., 2007; Li et al., 2008; Nagel et al., 2008; Frank et al., 2010; Satariano et al., 2010; King et al., 2011; Cheng et al., 2020).

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A walkable built environment, characterized by easy access to facilities, a well-connected street network, open spaces, and safe roads, has been identified as an ideal setting (Clarke et al., 2012; 2015; Cerin et al., 2017; Wörn, 2017). This environment is conducive to cognitive enrichment, fostering attention, social interactions, positive emotions, and offering educational activities that may contribute to resilience against cognitive impairments (Oveisgharan et al., 2020; Zhou et al., 2022). Studies indicate that residing in walkable neighborhoods tend to engage in more walking compared to those in less favorable environments (Michael et al., 2006; Lee et al., 2009; Kerr et al., 2012). Key features of walkable neighborhoods include smaller block sizes and denser street networks, providing more route choices and encouraging outside walking (Li et al., 2005; Lee et al., 2009; Satariano et al., 2010; King et al., 2011; Rosso et al., 2011). Additionally, the presence of pedestrian-friendly infrastructure such as wider sidewalks, railings, and isolated greenery, which enhance safety and protect senior pedestrians from motor traffic, can influence perceived safety, gait speed, and walking behaviors (Ståhl et al., 2013; Brookfield and Tilley, 2016; Duchowny et al., 2018). Conversely, negative environmental aesthetics, such as disorderly garbage, a deteriorating neighborhood scene, and chaotic traffic, have been linked to reduced walking frequency or duration (Borst et al., 2009).

Furthermore, the majority of existing studies discussed earlier employ regression models to examine the influence of street environmental factors on walking behaviors and activities, assuming linear effects (Forsyth et al., 2008; Saelens and Handy, 2008). Yet, the notion that environmental factors consistently evoke either solely negative or positive effects on walking behavior may not hold. Some studies suggest the potential for non-linear effects, highlighting a limitation of traditional regression models in thoroughly examining such complex relationships (Cheng et al., 2020; Cao and Tao, 2023). Machine learning models excel in capturing the complex non-linear relationships among variables, and a comparative analysis between these advanced models and traditional regression models holds the potential to provide more comprehensive insights. It is worth noting, however, that there is a scarcity of studies applying these advanced models to understand the impact of street environmental factors on walking route choices.

2 Data and methods (“H1”) (12p times new roman)

The participants in the study were recruited from four contiguous neighborhoods within the Yangpu district in Shanghai, China. Each of the four chosen neighborhoods exhibits a demographic composition with around 40% of residents aged over 60, along with a variety of street characteristics. In this research, the unit of analysis is the street segment, defined as a portion of roadway situated between two intersections. This choice is informed by the consideration that a route between two stops may span multiple street segments, making this unit more suitable for the analysis and modeling of walking route choices, as emphasized in prior studies (Borst et.al., 2009; Brookfield and Tilley, 2016). All of the 1,055 street segments within the 400-m buffer zone of the four neighborhoods are selected as the study area. This buffer size efficiently encompasses all reported walking paths, ensuring a comprehensive assessment of the chosen street segments within the study area. Eventually, we collected 133 valid samples (a response rate of 66.5%) from our survey. And 10 variables were chosen to measure the walkability of the study area.

Table 1. Description of selected segment-level environmental characteristics

Characteristics		Measurements	Variables
Segment choice		Calculated in the Dethmap software using $R = 400$ m	Continuous variable
Segment integration		Calculated in the Dethmap software using $R = 400$ m	Continuous variable
Width and length	Segment width (excluding sidewalks)	Calculated based on the map of Shanghai (V3.2)	Continuous variable (m)
	Segment length	Calculated based on the map of Shanghai (V3.2)	Continuous variable (m)
	Sidewalk width	Calculated based on the map of Shanghai (V3.2)	Continuous variable (m)
Street wall transparency		Calculated using the following equation: (category 1 *1.25 + category 2 *1 + category 3 *0.75) divided by the total length of the segment (Lopez, 2003)	Continuous variable (%)
Facility density	Retail	Calculated as the number of facilities in the segment divided by the total length of the segment	Continuous variable (%)
	Entertainment		
	Public service		
Traffic safety facility density	Guard rail	Calculated as the ratio of the length of safety facilities and the total length of the segment	Continuous variable (%)
	Street greenery		
Street wall continuity		Calculated as the ratio of the length of the front line of the zoning lot and the segment	Continuous variable (%)
Physical disorder density		Calculated as the number of the disorders divided by the length of the segment	Continuous variable (%)
Environment cue		Calculated as 1 if the segment has landmarks (e.g., sculptures, fountains, distinctive buildings, gardens, benches, and rest areas) or wayfinding signs and maps, and 0 otherwise	Dummy variable
Age-friendly design		Calculated as 1 if the segment has age-friendly facilities (e.g., public toilets, seating, crosswalks, smooth and even pathway, and street lighting), and 0 otherwise	Dummy variable

3 Modeling the relationships between segment-level environmental characteristics and walking route choices ("H1") (12p times new roman)

The random forest machine learning model was used to build regression models for examining the impacts of environmental street characteristics on walking route choices. Specifically, the dependent variable was the number of times each street segment was traversed by participants, while the independent variables were the environmental characteristics of the respective segments. The random forest model comprises a large ensemble of decision trees, each serving as an individual predictive model. These trees are subsequently combined to yield a more accurate and robust prediction (Breiman, 2001). A notable feature of this model is the generation of numerous random trees, ensuring a degree of uncorrelation among them. This randomness is achieved through techniques such as bootstrapping for training sample selection and random feature selection. Bootstrapping involves the random extraction, with replacement, of training data samples for each tree. Consequently, some observations may appear more than once, while others may be absent in the sample (Cheng et al., 2020). Another strategy for generating uncorrelated trees is through feature randomness. Instead of using all features (i.e., environmental characteristics listed in Table 2), each tree selects a random subset of features. This introduces more variation among the trees, resulting in a diverse forest with low correlations among individual trees. The final prediction is derived by averaging the predictions from each tree.

The random forest model includes a procedure to rank variable importance, which essentially reflects the marginal effect of a given environmental characteristic of the segment on the likelihood of it being chosen when controlling for the average effects of all other variables in a model. This relative importance of a given variable is measured by the total reduction of the mean square error (MSE) brought by that variable, formulated as follows:

$$VI_i = \frac{1}{n}\sum\nolimits_t (OOB_{MSE}^t - OOB_{MSE,perm_i}^t)$$

where VI_i represents the variable importance of a given environmental street characteristic i, n is the number of trees in the random forest model, OOB_{MSE}^t is the mean square error of the original tree t, and $OOB_{MSE,perm_i}^t$ is the mean square error after the replacement of variable i. The MSE is formulated as follows:

$$MSE = \frac{1}{n}\sum_{m=1}^{M} (y_m - \widehat{y_m})$$

where m represents the number of leaves in the tree, y_m represents the predicted usage frequency of street segments in the study area, and $\widehat{y_m}$ represents the observed usage frequency of street segments in m pieces.

Moreover, the random forest model allows for the identification of partial dependence between the outcome (e.g., the number of times a given street segment is chosen) and explanatory variables (e.g., environmental characteristics of the street segment), directly from the data without imposing distribution assumptions (Cheng et al., 2020). The results can help interpret whether the effects of environmental street characteristics on the walking route choices of older adults with SCD exhibit linear or non-linear patterns.

4 Results

4.1 Relative importance of segment-level environmental characteristics

Given the limited utilization of segments by participants (77 out of 1,055) in the study area, we focused the street segments within a 200 m buffer around the four neighborhoods for the random forest model, resulting in 140 segments for subsequent analyses. The RandomForestRegressor from the python package scikit-learn (Pedregosa et al., 2011) was employed for model development. Prior to building the random forest model, a variance inflation factor (VIF) analysis was conducted to assess multicollinearity among segment-level environmental characteristics. All variables listed in Table 1 exhibited a VIF value of no more than five, indicating the absence of significant multicollinearity (Craney and Surles, 2002). Consequently, all these variables were retained in the final model. The model was configured with 100 trees, 5 splitting variables, and a maximum tree depth of 50. The determination of these parameter values was based on considerations of model MSE and computation time, resulting in a final model with an MSE of 0.356 and pseudo-R^2 of 0.549.

The importance of segment-level environmental characteristics in influencing walking route choices is presented in Table 3.

Table 2. Comparative results of the random forest and Poisson regression models

	Random forest model		Poisson regression model	
Variables	Relative importance (%)	Ranking	Coefficients	Significance
Segment width	34.09	1	0.512	0.000***
Segment choice	18.85	2	0.474	0.000***
Guard rail density	13.05	3	-0.016	0.724
Sidewalk width	10.16	4	0.297	0.000***
Street wall continuity	8.65	5	0.076	0.073
Street wall transparency	4.34	6	-0.058	0.309
Physical disorder density	4.10	7	0.433	0.000***
Segment length	3.60	8	0.303	0.000***
Segment integration	1.92	9	-0.064	0.350
Retail density	0.52	10	-0.169	0.015*
Public service facility density	0.42	11	-0.209	0.001**
Entertainment facility density	0.17	12	-0.162	0.003**
Street greenery	0.07	13	-1.042	0.000***
Environment cue	0.03	14	0.010	0.917
Age-friendly design	0.03	15	-0.098	0.400
Pseudo-R^2	0.549		0.271	
MSE	0.356		1.153	

Note: * p-value ≤ 0.05, ** p-value ≤ 0.01, *** p-value ≤ 0.001.

4.2 Comparative analysis with the Poisson regression model

As many prior studies have predominantly employed regression models that assume linear relationships between independent and dependent variables, we opted for Poisson regression as one of these traditional linear regression models, given the count data nature of the dependent variable (segment usage frequency). We compare the results from the Poisson regression model with those from the random forest model to assess the disparity in goodness-of-fit between linear and non-linear models. Results show that the Pseudo-R^2 of the Poisson regression model (0.271) is considerably smaller than that of the random forest model (0.549). Moreover, the random forest model demonstrates significantly lower prediction error than the Poisson regression model (0.356 vs. 1.153). These outcomes demonstrate the superior performance of the random forest model over the linear regression model in understanding the effects of segment environmental characteristics on the recreational walking route choices.

5 Discussion and Conclusions

The random forest model reveals complex, non-linear effects of these segment characteristics on walking route choices. Unlike the commonly assumed linear effects in existing studies, such as the Poisson regression model in this research, the built environment's effects on walking route choices exhibits periodic changes, transitioning from positive to negative. This complexity suggests that devising context-specific solutions can be challenging, as the non-linear effects of these variables demonstrate a mechanism that is more complex than commonly expected. These findings highlight the importance of considering such non-linear effects in the built environment when designing walkable streets. Policies aimed at initiatives like widening streets and sidewalks, or enhancing street accessibility and connectivity should be approached with caution.

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