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# To walk or not to walk? Examining non-linear effects of streetscape greenery on walking propensity of older adults

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**Abstract:** Population aging is a conspicuous demographic trend shaping the world profoundly. Walking is a critical travel mode and physical activity for older adults. As such, there is a need to determine the factors influencing the walking behavior of older people in the era of population aging. Streetscape greenery is an easily perceived built-environment attribute and can promote walking behavior, but it has received insufficient attention. More importantly, the non-linear effects of streetscape greenery on the walking behavior of older adults have not been examined. We therefore use readily available Google Street View imagery and a fully convolutional neural network to evaluate human-scale, eye-level streetscape greenery. Using data from the Hong Kong Travel Characteristic Survey, we adopt a machine learning technique, namely random forest modeling, to scrutinize the non-linear effects of streetscape greenery on the walking propensity of older adults. The results show that streetscape greenery has a positive effect on walking propensity within a certain range, but outside the range, the positive association no longer holds. The non-linear associations of other built-environment attributes are also examined.

**Keywords:** Streetscape greenery; Big data; Machine learning; Random forest; Travel behavior; Walking behavior; Population aging

## 1. Introduction

The aging of the population, as a result of rising life expectancy, a decreasing fertility rate, and the aging of baby boomers (born between 1946 and 1964), is profoundly shaping a wide variety of regions around the world (e.g., Japan and Hong Kong). The absolute number and percentage of older people worldwide are ballooning. In 2019, there were 700 million older adults (defined as people aged ≥ 65) worldwide. By 2050, this number will nearly double to 1.3 billion. Additionally, the percentage of older people was 9.1% in 2019 and is predicted to climb to 15.9% in 2050 (United

Nations, 2019). Similarly, Hong Kong is facing the issue of population aging and dramatic and unprecedented changes in its demographic profile. Second only to Japan (28.4% in 2020, topping the global list) in the Asian context, Hong Kong has a high percentage of older people (18.2% in 2020). The percentage of its older people is predicted to grow to 34.7% in 2050 (United Nations, 2019).

Older people's mobility has been widely documented to be closely related to their participation in activities, social integration, physical and psychological health, and life satisfaction (Alsnih and Hensher, 2003; Metz, 2000; Chen et al., 2021). Their mobility is a determinant of quality of life and subjective wellbeing (Banister and Bowling, 2004). For older adults, an insufficient level of mobility leads to difficulty in participating/engaging in social activities and interacting with the wide community and, consequently, low morale, depression, and loneliness (Wong et al., 2018).

Walking is a form of active mobility (low-intensity physical activity) for residents and a travel mode with considerable economic, environmental, social, safety, and health advantages (Frank et al., 2007; Heath et al., 2012; Sælensminde, 2004; Wong et al., 2021). Walking has thus received much attention from governments, non-government organizations, and researchers. It has been advocated and promoted universally. As Cervero and Kockelman (1997) state, a paramount transportation objective is diverting travel demand from motorized to active modes such as walking. Moreover, walking is a critical travel mode for older adults, who generally have limited access to cars (Hu et al., 2013; Yang, 2018), in many locations (e.g., Chinese cities) (Cheng et al., 2019b; Liu et al., 2021b; van Wee and Handy, 2016). This is particularly true for Hong Kong. Owing to its mixed land use, pedestrian-friendly urban design, and high walkability, Hong Kongers have a predilection for and habit of walking, as evidenced by Hong Kongers taking the highest number of walking steps all over the world (Althoff et al., 2017).

Urban greenery may facilitate physical activity (due in part to humankind's biophilia nature) and alter people's walking behavior (Lu et al., 2018). Traditionally, its evaluation heavily relies on in-person assessments, field observations, aerial photography, and remote sensing imagery. However, these methods have limitations, such as high labor intensity, a restriction to small areas, a restriction to a bird's eye (overhead) view, and the inability to represent the human scale (Kang et al., 2020). Fortunately, owing to the availability of street-view imagery data and the rapid development of urban analytics, streetscape greenery has garnered increasing attention from researchers (especially those in the public health field) in recent years. We can now efficiently and accurately estimate streetscape greenery from street-view imagery (Kang et al., 2020).

Existing literature has extensively emphasized the effects of socio-demographic characteristics and built-environment attributes (e.g., population density and street connectivity) on the travel behavior of older adults. However, few studies have evaluated the role of streetscape greenery (Yang et al., 2020; Yang et al., 2019; Zang et al., 2020). More importantly, most, though not all, of these studies have assumed a pre-determined (often linear) relationship between travel behavior and its contributory factors. Nevertheless, the connection between the built environment and the travel behavior of older people may be non-linear (Ding et al., 2019; Liu et al., 2021a; van Wee and Handy, 2016). This non-linearity can be explained by the peer effect (or collective socialization) and travel utility (Cheng et al., 2020a; Galster, 2018; Mokhtarian and Salomon, 2001). In recent years, pioneering research has focused on the issue of non-linearity (Cheng et al., 2020a; Ding et al., 2018b; Ding et al., 2018c; Zhang et al., 2020). However, to our best knowledge, only one study (Cheng et al., 2020a) concentrates on the non-linearity of the connection between the built environment and the travel behavior of older people. No studies on the effect of streetscape greenery on travel behavior have considered the issue of non-linearity. As ignoring a genuinely non-linear effect may result in misunderstandings and erroneous practical implications (Cheng et al., 2020a), delving deeper into the non-linearity issue is crucial.

To address the above issues, we use data from the Hong Kong Travel Characteristic Survey (TCS) 2011 and Google Street View (GSV) imagery (detailed in Section 3) to assess the walking propensity (or propensity of walk trip-making, propensity to walk) of older people and streetscape greenery, respectively. A random forest model is adopted to evaluate the non-linear effects of streetscape greenery on walking propensity. A binary logistic regression model is generated to make a comparison with the random forest model. Notably, socio-demographic and built-environment attributes (measured by TCS 2011 data or geo-data) are controlled. The contributions of this study are (1) the examination of the connection between streetscape greenery and older people's walking propensity; (2) the scrutinization of the non-linear and threshold effects of streetscape greenery on travel behavior for the first time; and (3) the assessment of the non-linear and threshold effects of built-environment attributes on older people's walking behavior.

The remainder of this paper is organized as follows. The ensuing section reviews the literature on the contributory factors of the walking behavior of older adults. Sections 3 introduces the data and methodology of random forest modeling. Section 4 presents the results of random forest modeling and compares them with the outcomes of logit modeling. Section 5 winds up the paper, discusses theoretical and practical implications, and summarizes research limitations.

## 2. Literature review

A voluminous body of the existing literature has confirmed the effects of the built environment on the walking behavior of older people. We conducted electronic searches in the database of Web of Science and retrieved pertinent articles published between 2006 and 2020. We first screened the papers by title and then by abstracts. We considered their relevance to this study and manually chose papers for detailed reviews.

Table 1 summarizes selected studies on the link between the built environment and the travel behavior of older people. Normally, socio-demographic characteristics (e.g., sex and income) are controlled to single out the effect of the built environment and remove the effects of confounders. Furthermore, the built environment is primarily measured either objectively or subjectively, but rarely both (Hou et al., 2020; Van Holle et al., 2016). Objectively assessed built-environment attributes have garnered the most attention.

The effects of a few built-environment attributes (e.g., population density and access to services) are relatively consistent. However, empirical findings (e.g., on walking facilities' effect) remain elusive, which can be attributed to differences in contexts, predicted and controlled variables, and research methodologies.

In terms of study areas, North American cities have received the most scholarly attention. Asian cities (e.g., Hong Kong and Nanjing) have gradually entered the public discourse in the past decade. Most, if not all, Asian studies were completed after 2010. Furthermore, as a characteristic of the built environment, streetscape greenery has only very recently been spotlighted (Yang et al., 2019; Zang et al., 2020), mainly because of (1) advances in the techniques for measuring greenery that can precisely and efficiently estimate the perceived greenery at the eye level, and (2) the availability of street-view imagery data, which can be downloaded from mapping websites freely. Most importantly, the non-linear effect of the built environment on the walking behavior of older people has seldom been investigated. The only exception is the work of Cheng et al. (2020a), which is published very recently. Additionally, Van Cauwenberg et al. (2011) and Cerin et al. (2017) offer systematic reviews and meta-analyses of previous studies on the effects of the built environment on the walking behavior of older people. Interested readers can refer to the two studies for a better understanding of this topic.

**Table 1**
Review of selected studies on walking behavior of older people and built-environment attributes.

| Reference | Context | Sample | Walking behavior measure(s) | Built environment measures | Modeling approach | Empirical findings |
|---|---|---|---|---|---|---|
| *North America* | | | | | | |
| Mendes de Leon et al. (2009) | Chicago, the U.S. | 4,317 people aged ≥ 65 | Walking time | Neighborhood disorder (e.g., littering, trash, vandalism, and crumbled sidewalks) | Multilevel linear regression model | Neighborhood disorder is adversely associated with walking time. |
| Shigematsu et al. (2009) | King County/Seattle, the U.S. | 360 people aged ≥ 66 | Transport walking time and recreational walking time | Population density, street connectivity, etc. | Partial correlation analysis | Land-use mix significantly impacts both transport walking time and recreational walking time. |
| Procter-Gray et al. (2015) | Boston, the U.S. | 745 people aged ≥ 70 | Transport walking propensity and recreational walking propensity | Access to the bus, access to the hospital, etc. | Logistic regression model | Transport walking is strongly associated with measures of access to facilities while recreational walking is not. |
| Maisel (2016) | New York, the U.S. | 121 people aged ≥ 65 | Walking time | Population density, land-use mix, street connectivity, etc. | Spearman rank correlation analysis | The built environment is insignificantly related to walking time. |
| Barnes et al. (2016) | British Columbia, Canada | 3,860 people aged ≥ 45 | Transport walking propensity | Walkability and transit access | Logistic regression model | Walkability and transit access are significantly correlated with walking-for-transport trip propensity. |
| Moniruzzaman et al. (2013) and | Montreal, Canada | 31,631 one-way home-based trips | Walking propensity | Population density, job density, etc. | Logistic regression model | Population density, job density, and land-use mix positively influence the |

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|---|---|---|---|---|---|---|
| Moniruzzaman and Páez (2016) | | made by people aged ≥ 55 | | | | propensity to walk. |
| Moniruzzaman et al. (2015) | Montreal, Canada | 13,127 people aged ≥ 65 | Walking trip frequency | Population density, land-use mix, activity locations, etc. | Ordered probit regression model | Walking trip frequency is significantly influenced by job density but not by population density. |
| *Europe* | | | | | | |
| Van Holle et al. (2014) | Ghent, Belgium | 438 people aged ≥ 65 | Transport walking time and recreational walking time | Walkability | Multilevel linear regression model | Walkability is positively related to transport walking time but insignificantly associated with recreational walking time. |
| Van Holle et al. (2016) | Ghent, Belgium | 438 people aged ≥ 65 | Transport walking time | Land-use mix, street connectivity, walkability, etc. | Multilevel linear regression model | Walkability and street connectivity significantly affect transport walking time. |
| Etman et al. (2014) | Spijkenisse, Rotterdam, the Netherlands | 408 people aged ≥ 65 | Walking time | Access to functional features, aesthetics, destination accessibility, etc. | Linear regression model | Access to functional features is significant associated with walking time. |
| Böcker et al. (2017) | Greater Rotterdam, the Netherlands | 147 people aged ≥ 65 | Walking propensity | Building diversity, green space cover, etc. | Logistic regression model | Building density is positively related to walking propensity. |
| *Australia* | | | | | | |
| Boruff et al. (2012) | Perth, Australia | 325 people living in 32 retirement villages | Walking trip frequency | Land-use exposure | Logistic regression model | Commercial and institution land exposure does not significantly influence walking trip frequency. |

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|---|---|---|---|---|---|---|
| Ghani et al. (2018) | Brisbane, Australia | 11,035 people aged 58 to 65 | Transport walking duration | Population density, street connectivity, etc. | Multilevel binary logistic regression model | The built environment has a larger walking time effect on older people than on younger counterparts. |
| *Asia* | | | | | | |
| Leung et al. (2018) | Hong Kong | 679 people aged ≥ 65 | Daily step counts | Land-use mix, access, etc. | Structural equation model | Land-use mix and street connectivity significantly affect daily step counts. |
| Yang et al. (2019) | Hong Kong | 10,700/1,083 people aged ≥ 65 | Walking propensity and walking time | Population density, land-use mix, access to recreational facilities, streetscape greenery, etc. | Two-level binary logistic regression model and two-level linear regression model | Streetscape greenery positively impacts walking propensity and walking time. |
| Zang et al. (2020) | Hong Kong | 180 able-bodied people aged ≥ 65 | Walking time | Population density, land-use mix, street connectivity, and streetscape greenery | Bivariate correlation analysis | Streetscape greenery positively affects walking time, but other built-environment variables do not. |
| Koh et al. (2015) | Singapore | 168 people aged ≥ 65 | Walking time | Presence of stairs/slope, scenery, directional sign, accessibility to opportunities within the neighborhood, etc. | Generalized linear regression model | Road crossing delays and access to shops and sheltered social interaction areas significantly affect walking time. |
| Hou (2019) | Singapore | Around 7500 people ≥ 55 | Non-work walking trip frequency | Population density, land-use mix, access to regional centers, access to the rail transit, access to cultural facilities, etc. | Zero-inflated ordered probit regression model | Access to regional centers is positively related to walking trip frequency. The built environment-travel link varies across older adult subgroups. |
| Hou et al. (2020) | Singapore | 1002 people aged | Daily walking trip | Population density, street | Multivariate | Perceived access to recreational |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | ≥ 55 | frequency | connectivity, transit accessibility, access to recreational facilities, etc. | ordered probit regression model | facilities is positively related to walking trip frequency. Objectively assessed and perceived built-environment variables jointly affect walk trip-making. |
| Cheng et al. (2020a) | Nanjing, China | 702 people aged ≥ 60 | Walking time | Population density, land-use mix, access to the bus, access to bike-sharing, etc. | Random forest | Built-environment attributes affect walking time in a non-linear manner, and they matter only at certain levels. |

## 3. Data and methodology

### *3.1. TCS 2011 data*

TCS 2011 is a wide-ranging and comprehensive travel survey that was conducted by the Transport Department of the Hong Kong government during September 2011 and January 2012. The TCS is conducted roughly every ten years. It includes three main surveys, namely household interview survey (for collecting the trip information of Hong Kong residents), stated preference survey (for identifying the contributory factors of transport mode choices for users), and hotel/guesthouse tourists survey (for gathering the trip-making characteristics and trip information of tourists who stayed in hotels/guesthouses). Among them, the household interview survey is the backbone of TCS 2011. The data from this survey were acquired from 101,385 residents in 35,401 randomly selected households on weekdays. The sampling rate of the TCS 2011 household interview survey is around 1.5%.

Akin to most large-scale official travel surveys, the TCS 2011 household interview survey collects much information on the respondents at three levels: (1). Household-level information (e.g., residential location, house type, monthly household income, the number of family numbers, and car availability); (2). household member-level information (e.g., age, sex, employment status, and industry engaged); and (3). trip-level information, namely the 24-hour trip document for every family member (e.g., trip origin and destination, trip mode, trip start time and end time, trip legs, and interchange locations). TCS 2011 includes the residential locations of respondents, and we therefore geo-code the data in the ArcGIS software (*Version 10.6*) for subsequent residence-centric built-environment measurement.

According to international standards (United Nations, 2019) and local conditions of Hong Kong (e.g., eligibility for social services specifically targeting older citizens) (Loo and Lam, 2012), this study defines older people as people aged $\geq$ 65. This definition is also used in the literature (Cheng et al., 2020b; Yang et al., 2019). We categorize the respondents of TCS 2011 into two groups: people who had done at least some walking (walking propensity = 1) in the reference 24 hours and those who had not done so (walking propensity = 0).

### *3.2. Streetscape greenery*

Street-view imagery describes the urban physical environment with a view highly similar to human vision and virtually represents a static 360-degree street-view panorama. It has particular advantages (e.g., high geographical coverage, few data bias, cost-effectiveness, time-effectiveness, and human-centered scale) over traditional data sources (Kang et al., 2020). GSV is the earliest online street-view service (initiated in 2007), covering cities in around 90 countries. Its data are collected by drive-by sensing cars equipped with Global Positioning System devices.

Using GSV imagery, the eye-level streetscape greenery index (or green view index), which reflects people's visual contact with, or exposure to, streetscape greenery, is estimated as follows. First, the residential locations of sampled older adults are geo-coded according to coordinates (longitude and latitude) into the ArcGIS platform. Second, all street segments near a residential location are automatically identified. Third, GSV-generating positions with a fixed spacing of 50 m are determined. Fourth, hundreds of thousands of GSV images are downloaded from the Google Maps website. For each GSV-generating position, four images that are mutually exclusive but collectively represent the 360-degree panorama are needed. Fifth, a machine learning technique (more specifically, fully convolutional neural network, see Fig. 1) (Long et al., 2015) is used to automatically distill greenery pixels from the street-view imagery

(Fig. 1). The streetscape greenery calculation formula for a GSV-generating position is

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

**Fig. 1.** Illustration of the GSV-based eye-level streetscape greenery estimation method

*3.3. Variables*

The selection of predictor variables is guided by the literature and data availability. Eight socio-demographic variables and six built-environment variables are selected. In addition to streetscape greenery (variable of our main focus), five built-environment control variables are chosen, as guided by the "5Ds" built-environment assessment framework (Ewing and Cervero, 2010). All the built-environment variables are measured within the ArcGIS framework using the geo-data from an online mapping service website, *OpenStreetMaps* (*https://www.openstreetmap.org*).

Table 2 gives the descriptions and summary statistics of the predicted and predictor variables. Sixty-three percent of older people had done at least some walking during the reference 24 hours, while the other thirty-seven percent had not done so.

**Table 2**

Descriptions and summary statistics of the predicted and predictor variables

| **Variable** | **Description** | **Mean/Percentage** | **Std. Dev.** |
|---|---|---|---|
| *Predicted variable* | | | |
| Walking propensity | Indicator variable; = 1 for having done some walking on the reference day, = 0 otherwise | 0.63 | |
| *Predictor variables: socio-demographics* | | | |
| House type | Indicator variable; = 1 for person living in a privately owned house, = 0 otherwise | 0.47 | |
| Household size | Number of family numbers | 2.76 | 1.38 |
| Male | Indicator variable; = 1 for male, = 0 for female | 0.49 | |
| Age | Age of older adults (unit: year) | 73.82 | 6.93 |
| Automobile | Indicator variable; = 1 for person with household car | 0.07 | |

| | | | |
|---|---|---|---|
| | availability, = 0 otherwise | | |
| Low-income household | Indicator variable; = 1 for person with monthly household income less than HK$ 15,000 | 0.57 | |
| Middle-income household (reference) | Indicator variable; = 1 for person with monthly household income between HK$ 15,000 and HK$ 50,000 | 0.37 | |
| High-income household | Indicator variable; = 1 for person with monthly household income no less than HK$ 50,000 | 0.06 | |
| *Predictor variables: built environment* | | | |
| Population density | Population density within the neighborhood (unit: $10^3$ people/km$^2$) | 47.98 | 32.95 |
| Land-use mix | Entropy for land uses within the neighborhood. = $\sum_i (p_i \ln p_i) / \ln N$, where $p_i$ is the proportion of the *i*-th land use, and N is the number of land use categories. In this study, three land uses (residential, office, and retail) are considered (N = 3). | 0.44 | 0.23 |
| Intersection density | Density of street intersections within the neighborhood (unit: 1/km$^2$) | 72.14 | 49.75 |
| Access to bus stops | Number of bus stops within 400 m | 20.10 | 11.34 |
| Access to recreational facilities | Number of recreational facilities within 400 m | 18.12 | 9.02 |
| Streetscape greenery | Green view index, calculated by the proportion of greenery pixels to total pixels (see Fig. 2) | 0.15 | 0.03 |
| Sample size | 10,700 | | |

### *3.4. Methodology*

The random forest (a.k.a., random decision forest) is among the most popular and powerful supervised machine learning algorithms. It can execute both classification and regression tasks and often performs better in the former (classification tasks) than in the latter (regression tasks). This ensemble machine learning algorithm based on the concept of "random decision forests," first proposed by Ho (1995), creates a forest with many trees for classification or regression.

Fig. 2 presents the random forest algorithm. The algorithm combines the simplicity of decision trees with flexibility, and only a subset of samples and predictor variables are used for a single tree. The algorithm thus reduces variance and is robust against noise and outliers, leading to better stability and accuracy. Meanwhile, the algorithm does not overfit data because of the law of large numbers, so it is unlikely to have poor accuracy on unseen data and can generalize well for training data. In stark contrast to traditional regression-based analyses, the random forest algorithm does not pre-determine a specific relationship between the predicted and predictor variables and thus has fewer restrictions. Consequently, it better represents the genuine relationship between the predicted and predictor variables. Moreover, the random forest algorithm handles missing values and maintains accuracy in the event of missing data.

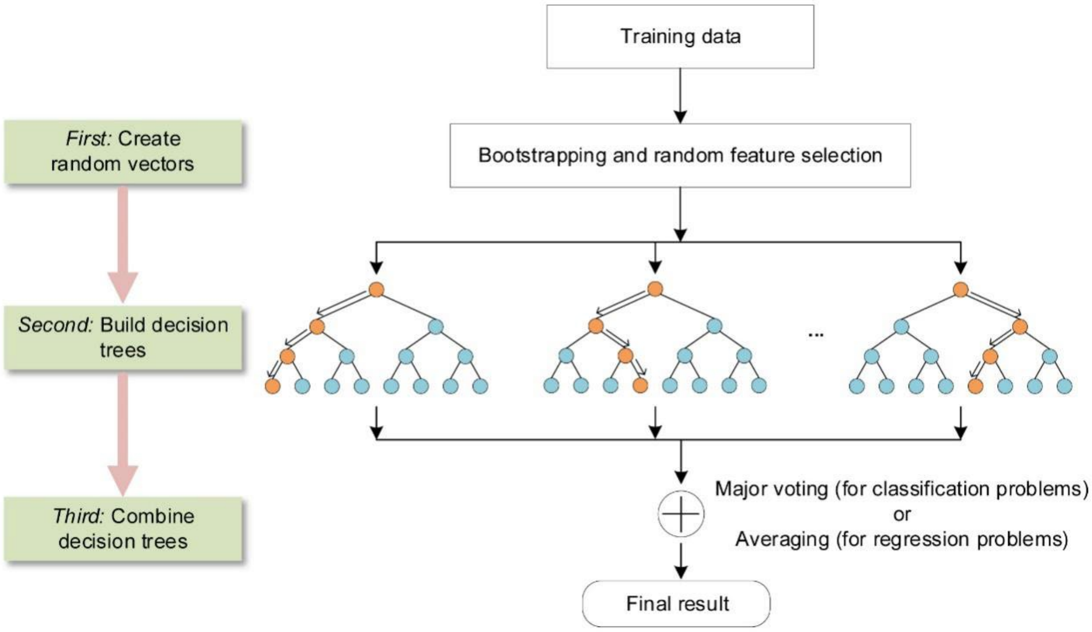


**Fig. 2.** Illustration of the random forest algorithm.
Source: Cheng et al. (2019a) and Cheng et al. (2020a)

In sharp contrast to traditional regression-based statistical analyses that pre-determine a (usually linear) relationship between the predicted and predictor variables, the random forest and most, if not all, other machine learning techniques do not produce *t*-statistics, *p*-values, and statistical significance indicators. Instead, a key result of random forest modeling is relative importance, which is the importance of each predictor variable in predicting the focal variable. Hence, the interpretation of random forest modeling results must be treated with caution. In addition to relative importance, random forest modeling produces partial dependence plots (PDPs) to characterize the relationship between the predicted and predictor variables, which depends on the levels of predictor variables.

Three parameters need to be specified or tuned before using the random forest algorithm. They are the maximum depth of a tree, the number of features (splitting variables) for each tree, and the number of trees (forest size). In this study, to obtain the optimal combination of the three parameters, we employ a widely used technique, namely grid search (Claesen and De Moor, 2015), rather than arbitrarily determining the parameters. We conduct the grid search as follows. First, we determine the ranges of the three parameters (from 1 to 20 for the maximum tree depth, from 2 to 10 for the number of features for each tree, and from 10 to 1000 with an interval of 10 for the number of trees). Second, we estimate a total of 18,000 (= $20 \times 9 \times 100$) possible combinations and test the model performance using out-of-bag error (Cheng et al., 2019a). After conducting the 18,000 tests, we find that the model performs best when the maximum depth of a tree is 12, the number of features for each tree is 3, and the number of trees is 850. Further analyses are conducted using this optimal model.

## 4. Results

### *4.1. Relative importance of predictor variables*

Table 3 presents the random forest results and shows the relative importance of predictor variables. Fig. 3 graphically describes the relative importance. The variable of primary interest, namely Streetscape greenery, has the second-highest relative importance (12.82%), exceeded only by Age (16.65%). This outcome supports the critical role of streetscape greenery in determining the walking propensity of older adults. Furthermore, the other "5Ds" built-environment variables closely follow Streetscape greenery in terms of relative importance (ranging from 9.27% to 10.55%). This result demonstrates that the "5Ds" framework is useful in capturing the built environment.

Collectively, the built-environment variables account for 62.89% of the total relative importance, while the socio-demographic variables constitute the other 37.11%. This result indicates that the walking propensity of older adults is primarily a function of the built environment and secondarily a function of the socio-demographic characteristics of older people. It is in agreement with the work of Cheng et al. (2020a), which deciphers the relationship between the built environment and the walking behavior of older adults in a Chinese city (Nanjing). Moreover, the result reinforces empirical findings from other regions (e.g., North America): built-environment variables have larger effects than socio-demographics on many travel outcomes (Ding et al., 2018a; Ewing and Cervero, 2001, 2010; Gim, 2013; Wang and Ozbilen, 2020).

**Table 3**

Predictor variables' relative importance calculated by the random forest

| **Variable category** | **Variable** | **Rank** | **Relative importance (%)** | **Total (%)** |
|---|---|---|---|---|
| Socio-demographics | House type | 12 | 1.79 | 37.11 |
| | Household size | 8 | 8.09 | |
| | Male | 10 | 3.22 | |
| | Age | 1 | 16.65 | |
| | Automobile | 11 | 2.03 | |
| | Household income | 9 | 5.33 | |
| Built environment | Population density | 5 | 9.92 | 62.89 |
| | Land use mix | 7 | 9.27 | |
| | Intersection density | 6 | 9.87 | |
| | Access to bus stops | 3 | 10.55 | |
| | Access to recreational facilities | 4 | 10.46 | |
| | Streetscape greenery | 2 | 12.82 | |

Note: The relative importance of household income is calculated by the sum of the importance of household income dummies.

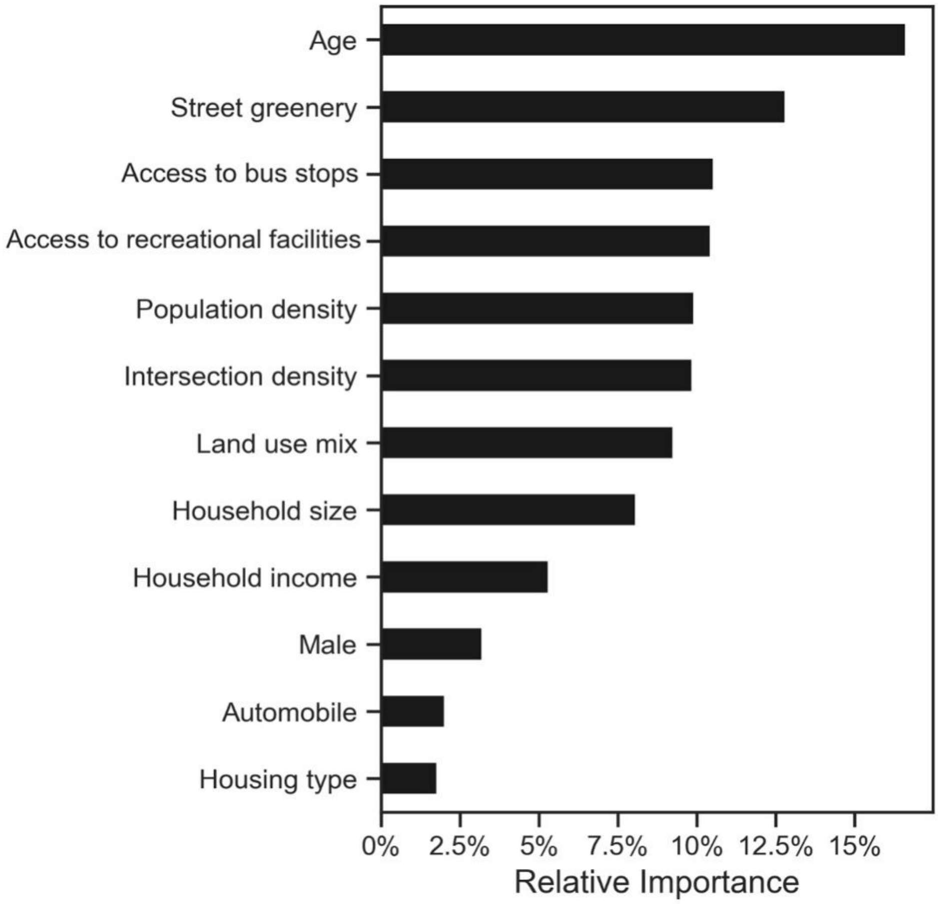


**Fig. 3.** Relative importance of predictor variables

*4.2. Non-linear effect of Streetscape greenery*

As previously mentioned, in addition to relative importance, random forest modeling produces PDPs for predictor variables. Fig. 4 shows the PDP of Streetscape greenery (the variable of dominant interest) and illustrates the non-linear effect of the streetscape greenery on the walking propensity of older adults. The x-axis of a PDP shows the distribution of the predictor variable. A smoothed curve (shown in red) is drawn to reduce the noise and better describe the relationship, following the work of Tao et al. (2020).

Fig. 4 offers strong evidence of the non-linear effect of the streetscape greenery on the walking propensity of older adults and demonstrates that the facilitating effect of the streetscape greenery on walking propensity is by no means unconditional and not always true. A green view index smaller than 0.24 is positively related to walking propensity. However, when the green view index exceeds 0.24, it has a limited (even slightly negative) effect on walking propensity. A possible explanation is that an ultra-high green view index often means the absence or insufficiency of other attractions for older adults.

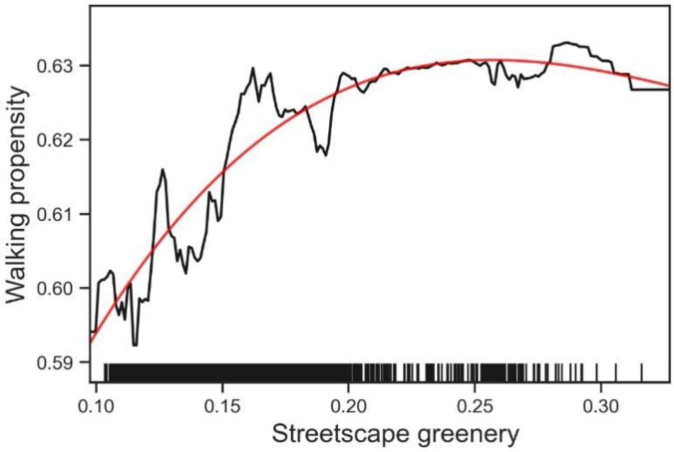


**Fig. 4.** Non-linear effect of streetscape greenery on walking propensity

*4.3. Non-linear effects of other built-environment variables*

Fig. 5 presents the PDPs of the other five built-environment variables. The positive effect of population density on walking propensity is observed when the population density is lower than 75,000 people/km$^2$ (Fig. 5a). It is reasonably inferred that a high population density always means that there are abundant opportunities nearby, thereby promoting walking behavior. However, the population density has marginal (slightly adverse) effects when it exceeds 75,000 people/km$^2$. A possible explanation is that a higher risk of injury is expected in ultra-dense areas (Cheng et al., 2020a).

Fig. 5b reveals the effect of the land-use mix on walking propensity. When the land-use mix index is smaller than 0.55, it mostly has a positive effect on walking propensity. This outcome matches our expectations and the literature (Cerin et al., 2017; Cheng et al., 2020a). A compelling explanation is that a high land-use mix index indicates that there are diverse opportunities in the neighborhood, satisfying the need for walking. However, this does not hold if the land-use mix index is over 0.55. That is, a negative relationship is observed if the land-use mix index ranges from 0.55 to 0.80.

Fig. 5c shows the effect of the density of street intersections (a street connectivity measure) on walking propensity. When the intersection density increases from 25/km$^2$ to 65/km$^2$, walking propensity increases sharply and reaches a peak value at 65/km$^2$. However, in other ranges, the intersection density has a marginal or even adverse effect on walking propensity. This interesting finding is largely consistent with Cheng et al. (2020a). The causes of the relationship are unclear, and more studies are needed to support or reject our results.

Figs. 5d and 5e illustrate the effects of access to bus stops and access to recreational facilities, respectively, on walking propensity. As expected, non-linear effects are again observed.

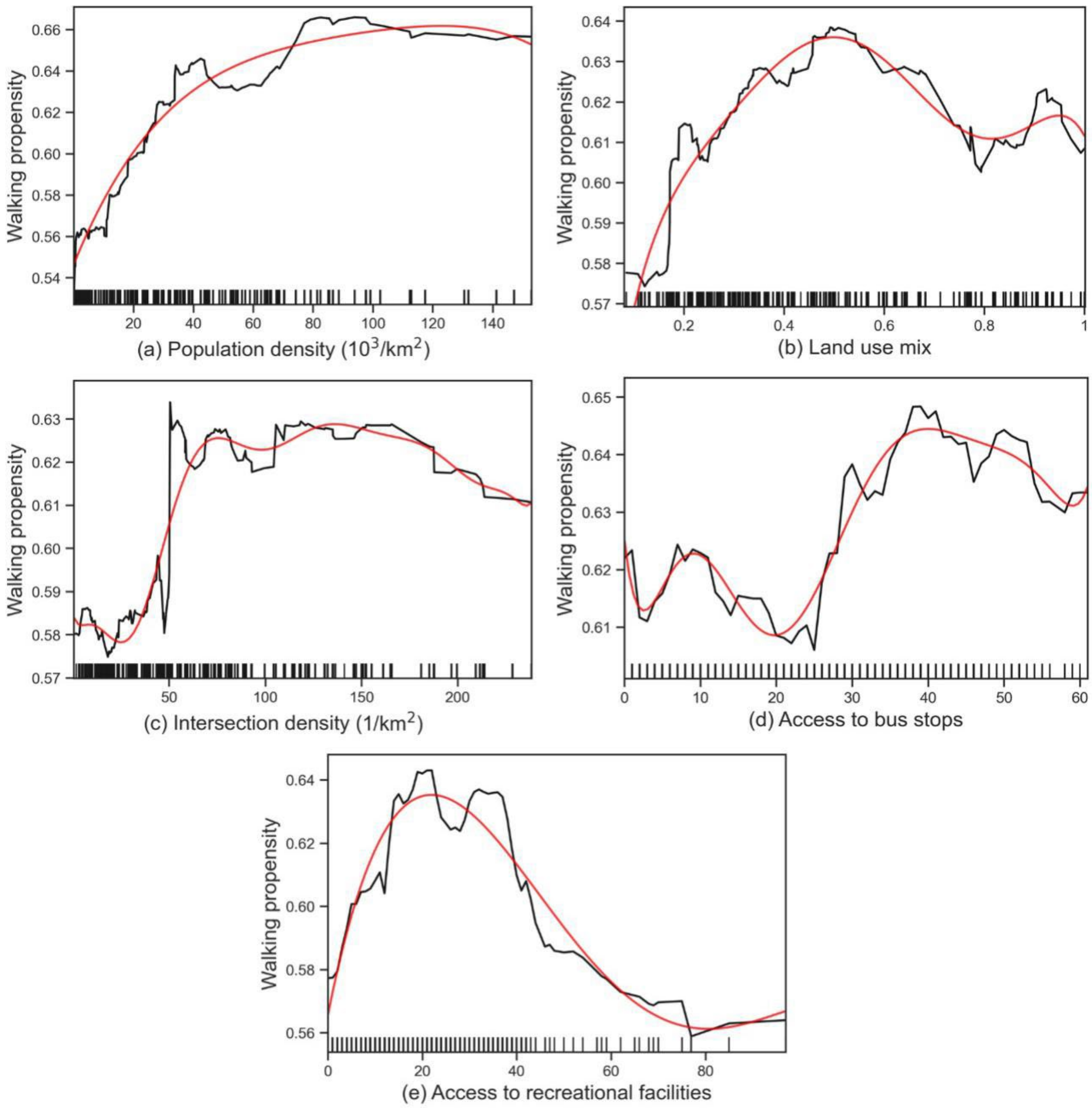


**Fig. 5.** Non-linear effects of other built-environment attributes on walking propensity

*4.4. Comparison of random forest modeling and binary logistic modeling*

We use 10-fold cross-validation to evaluate the performances of random forest modeling and binary logistic modeling. (Pearson's correlation analysis results and the binary logistic modeling results are provided in Tables A1 and A2, Appendices.) Two common metrics of classification, namely accuracy and precision (Powers, 2020), are used. The formula of the two metrics are as follows:

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

$$Precision = \frac{\sum_{i=1}^{N} TP_i}{\sum_{i=1}^{N} TP_i + FP_i}$$

where $N$ is the number of samples in the validation set, $TP_i$ is true positive (the observed walking propensity is 1, and the predicted walking propensity is also 1), $TN_i$ is true negative (the observed walking propensity is 0, and the predicted walking propensity is also 0), $FP_i$ is false positive (the observed walking propensity is 0, but the predicted walking propensity is 1), $FN_i$ is false negative (the observed walking propensity is 1, but the predicted walking propensity is 0).

**Table 4**
Comparison of results from the random forest and the binary logistic regression model

| **Model** | **Accuracy** | | **Precision** | |
|---|---|---|---|---|
| | **Mean** | **Std.** | **Mean** | **Std.** |
| Random forest | 0.640 | 0.013 | 0.666 | 0.012 |
| Binary logistic model | 0.639 | 0.010 | 0.646 | 0.008 |

Table 4 presents the 10-fold cross-validation results. It is seen that random forest modeling outperforms the traditional logit modeling for both metrics.

## 5. Conclusions and discussions

The aging of the population has become a popular phenomenon in many cities worldwide (Jing et al., 2021), such as Hong Kong. Given that walking is a prevalent travel mode for older adults and has multiple health and wellbeing benefits, determining the correlates of the walking behavior of older adults is of paramount importance. Furthermore, as an easily perceived built-environment attribute, streetscape greenery has seldom been investigated in the travel behavior literature of older adults but can now be accurately estimated using cutting-edge machine learning techniques. Therefore, this study scrutinizes its non-linear and threshold effects on the walking propensity of older people in Hong Kong by adopting random forest modeling. The findings of this study are that (1) the walking propensity of older adults is primarily a function of the built environment and secondarily a function of the socio-demographic characteristics of those older people; (2) streetscape greenery has considerable importance in predicting walking propensity; (3) streetscape greenery has non-linear and threshold effects on walking propensity; (4) a green view index smaller than 0.24 is positively related to walking propensity. However, when the green view index exceeds 0.24, it has a limited (even slightly adverse) effect on walking propensity; and (5) built-environment characteristics affect walking propensity in a non-linear way.

This study has profound methodological and practical implications, and its findings will be of great interest to decision-makers, researchers, and urban planners/designers. On the one hand, research on the non-linear relationship between travel behavior and the built environment has proliferated in the last four years. This study and its counterparts collectively illustrate that pre-determining a relationship between travel behavior and the built environment and overlooking the possible presence of complexity in the relationship result in unreliable, deceptive parameter estimates and lead to erroneous practical implications. Therefore, using techniques that are more sophisticated than traditional regression-based analyses, such as machine learning techniques, can help us to better understand the complex link between the built environment and travel behavior. On the other hand, this study benefits current practice. Traditionally, due to the dominance of linear association studies (or the insufficiency of non-linear association studies), decision-makers and urban planners/designers often have limited knowledge of the dose-response effect between built-environment characteristics and travel outcomes (and other indicators, such as health, economic, and equity) and assume linear effects. It is tempting for them to focus myopically on merely increasing the value of a specific favorable characteristic (e.g., blindly uplifting urban greenery or offering green spaces). On the basis of the evidence gathered in this study and similar research, modifying the physical environment to a specific level may be optimal. As an example, for a while, the conventional thinking was that the population density has a monotonically positive effect on walking activity because a high density always means that there are abundant opportunities nearby, promoting walking behavior. However, as Lu et al. (2019) and Cheng et al. (2020a) indicated, the effect of population density on walking becomes negative after it exceeds a certain threshold, or a population density within a certain range is optimal in terms of promoting walking behavior. An explanation is that an ultra-dense area induces crowdedness and higher risks of injury, discouraging walking (Cheng et al., 2020a). Likewise, this study implies that a green view index of 0.24 is optimal from the perspective of promoting the walking activity of older adults. Hence, the traditional approach of immoderate increases may be ineffective and even bring about side effects, and keeping built-environment variables within a certain range may be the most effective approach. The effective range of a variable should be carefully assessed in theoretical and empirical studies.

Owing to the rapid development of urban analytics, the built environment can be now measured at a more nuanced, fine-grained, human-centered scale and quantified more accurately and comprehensively. Using GSV imagery to sense and quantify the built environment (more broadly, the physical or living environment) and estimate the eye-level real-world landscape (e.g., streetscape greenery, sky view, and street canyon) has become increasingly popular in recent years. We believe that the use of street-view imagery can substantially enrich our understanding of the connection between the built environment and travel behavior. Most empirical studies can be devoted to this issue. We argue that the use of street-view imagery does supplement, augment, and advance (but by no means fully replaces) traditional built-environment assessment methods. The traditional methods can still play an essential role because of their ease of use.

Despite providing many insightful findings, this study has limitations. First, Hong Kong is an ultra-dense, mixed land-use city (Bao et al., 2020). The transferability or generalizability of the findings of this study to other places is unclear. More empirical studies conducted in other settings are needed to provide consistent/conflicting evidence and reach more persuasive conclusions. Second, there may be the combined or synergistic effects of built-environment variables (e.g., streetscape greenery and population density) on promoting walking behavior (Ding et al., 2018a; Wang and Ozbilen, 2020), which this study fails to analyze. Third, the empirical results of this study (e.g., relative importance and PDP) are surely conditional on the independent variables. Theoretically, the choice of independent variables should be mutually exclusive but collectively exhaustive. In practice, however, this cannot be accomplished, and the missing variable bias commonly exists. In other words, we cannot control for all factors contributing to the dependent variable. Although this study is well informed by the literature in the choice of contributory factors, more potential factors can be incorporated into the model to increase accountability. Fourth, in reality, people see and experience greenery in three dimensions. Hence, the greenery exposure estimates based on GSV imagery cannot fully capture human perceptions (Kang et al., 2020). We suspect that this difference only affects our results in a marginal way. Nevertheless, we believe that street-view imagery data are far from perfect for environmental exposure, so more sophisticated research methods (e.g., virtual reality and wearable cameras) can be used to assess population exposure to greenery and other elements with the advance of science and technology.

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**Appendix**

**Table A1.**

Pearson's correlation coefficient of predictor variables

| Variable | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 | X11 | X12 | X13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| House type (X1) | 1 | | | | | | | | | | | | |
| Household size (X2) | <0.01 | 1 | | | | | | | | | | | |
| Male (X3) | -0.02 | 0.04 | 1 | | | | | | | | | | |
| Age (X4) | -0.01 | -0.09 | -0.03 | 1 | | | | | | | | | |
| Automobile (X5) | 0.15 | 0.21 | <0.01 | -0.04 | 1 | | | | | | | | |
| Low-income household (X6) | -0.15 | -0.55 | -0.03 | 0.14 | -0.23 | 1 | | | | | | | |
| High-income household (X7) | 0.20 | 0.26 | <0.01 | -0.04 | 0.32 | -0.29 | 1 | | | | | | |
| Population density (X8) | 0.02 | 0.02 | -0.01 | -0.01 | -0.08 | -0.01 | -0.04 | 1 | | | | | |
| Land-use mix (X9) | 0.36 | -0.02 | <0.01 | 0.03 | <0.01 | -0.03 | 0.05 | -0.04 | 1 | | | | |
| Intersection density (X10) | 0.29 | -0.02 | -0.01 | 0.03 | -0.05 | -0.01 | 0.01 | 0.61 | 0.50 | 1 | | | |
| Access to bus stops (X11) | 0.05 | -0.02 | -0.02 | 0.04 | -0.08 | 0.03 | -0.04 | 0.40 | 0.29 | 0.50 | 1 | | |
| Access to recreational facilities (X12) | -0.02 | <0.01 | -0.01 | 0.01 | -0.03 | -0.01 | <0.01 | 0.22 | 0.23 | 0.35 | 0.40 | 1 | |
| Streetscape greenery (X13) | -0.09 | -0.01 | 0.01 | <0.01 | 0.04 | 0.04 | -0.03 | -0.42 | -0.21 | -0.53 | -0.49 | -0.28 | 1 |

**Table A2.**

Binary logistic modeling results

| **Variable** | **Coefficient** | **Standard deviation** | ***p*-value** |
|---|---|---|---|
| House type | $-0.164^{**}$ | 0.047 | <0.001 |
| Household size | $0.150^{**}$ | 0.019 | <0.001 |
| Male | $-0.309^{**}$ | 0.041 | <0.001 |
| Age | $0.048^{**}$ | 0.003 | <0.001 |

| | | | |
|---|---|---|---|
| Automobile | -0.412** | 0.086 | <0.001 |
| Low-income household | 0.185** | 0.052 | <0.001 |
| Middle-income household | Reference | | |
| High-income household | -0.504** | 0.093 | <0.001 |
| Population density | 0.005** | 0.001 | <0.001 |
| Land-use mix | 0.315** | 0.103 | 0.002 |
| Intersection density | 0.002* | 0.001 | 0.029 |
| Access to bus stops | 0.007** | 0.002 | 0.003 |
| Access to recreational facilities | 0.003 | 0.003 | 0.213 |
| Streetscape greenery | 3.316** | 0.751 | <0.001 |
| Constant | -4.404** | 0.290 | <0.001 |
| *Performance statistics* | | | |
| Pseudo $R$-squared | 0.044 | | |
| Log-likelihood | -6738.3 | | |

Note: ** Significant at the 1% level. * Significant at the 5% level.

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