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Examining the association between the built environment and pedestrian volume using street view images

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ABSTRACT

Many studies have confirmed that the characteristics of the built environment affect individual walking behaviors. However, scant attention has been paid to population-level walking behaviors, such as pedestrian volume, because of the difficulty of collecting such data. We propose a new approach to extract citywide pedestrian volume using readily available street view images and machine learning technique. This innovative method has superior efficiency and geographic reach. In addition, we explore the associations between the extracted pedestrian volume and both macro- and micro-scale built environment characteristics. The results show that micro-scale characteristics, such as the street-level greenery, open sky, and sidewalk, are positively associated with pedestrian volume. Macro-scale characteristics, operationalized using the 5Ds framework including density, diversity, design, destination accessibility, and distance to transit, are also associated with pedestrian volume. Hence, to stimulate population-level walking behaviors, policymakers and urban planners should focus on the built environment intervetions at both the micro and macroscale.

1. Introduction

Global urbanization in the last few decades has resulted in car dependency (Wang & Zhou, 2017) and more sedentary lifestyles among urban residents (Monda et al., 2007; Wang, Feng, et al., 2020). Therefore, the problem of physical inactivity has attracted the attention of researchers and public health officials in recent years (Hallal et al., 2012). According to a worldwide study, about one-third of urban adults do not meet the recommended 150 min of moderate-to-vigorous physical activity per week (Hallal et al., 2012; Kohl et al., 2012). Among all types of physical activities, walking is arguably the most common and convenient, because it requires no specialized equipment, venue, or skills and can be easily incorporated into one's daily routine (Eyler et al., 2003; Foster et al., 2018; Lee & Buchner, 2008; Lu, Sarkar, & Xiao, 2018). Walking behaviors play a vital role for active living, urban vitality, and sustainable mobility (Cerin et al., 2007; Gauvin et al., 2008; Jacobs, 1961; Sung et al., 2015). Moreover, empirical evidence suggests that regular walking can substantially improve health by, for example, reducing the risk of stroke and obesity, and improving bone health and cognitive function (Lee et al., 2012; Sallis et al., 2012).

Promoting walking and pedestrian volume has become a priority in public health and urban planning worldwide (Chen et al., 2020; Kohl et al., 2012). In addition to educational interventions at personal level, there is increasing attention towards the role of built environment on fostering walking behaviors (Handy et al., 2002; Jacobs, 1961; Whyte, 1980). Synthesis reviews have provided solid evidence that the built environment characteristics can impact walking (Barnett et al., 2017; Day, 2016; Saelens & Handy, 2008; Sallis et al., 2012). However, most empirical studies evaluate individual-level walking behaviors (e.g., walking trips) by surveys and questionnaires, which has inherent methodological limitations such as prone to recall bias and social desirability bias, time-consuming, and labor-intensive. Furthermore, previous studies were often conducted in limited research scale such as several residential neighborhoods and street segments. To date, scant attention has been paid to population-level walking behaviors (e.g., collective pedestrian volume in a street block) at a large geographic area

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because of the difficulty of collecting such data (Cesare et al., 2019; Hankey et al., 2017). The collective walking behavior can stimulate urban vitality, and it also has many social, economic, and environmental benefits (Lee et al., 2012; Sallis et al., 2012). In addition, most studies measure the built environment characteristics through either macro-scale D variables (e.g., Density, Diversity, Destination accessibility) or micro-scale streetscape features (e.g., greenery, sidewalk).

Recent advances in freely available street view images and machine learning have stimulated urban studies at finer granularity and larger scale (Biljecki & Ito, 2021; Kang et al., 2020; Rzotkiewicz et al., 2018). Researchers have increasingly employed street view images as an effective alternative to audit the built environment characteristics at street level. Moreover, street view image has been validated with good accuracy to estimate pedestrian volume (Chen et al., 2020; Yin et al., 2015). Thus, it is promising to examine the association between the built environment and pedestrian volume at a larger area with finer-grained details in different urban contexts. By assessing population-level walking behaviors, urban planning can better formulate planning interventions to promote regional physical activity.

Due to the current research gaps, this study investigated the association between street-level built environment and population-level walking behaviors (i.e., pedestrian volume) using street view images collected in Shanghai, China. Both pedestrian volume and street-level built environment factors are assessed by integrating street view images with machine learning. This work extends previous research in several respects. First, it contributes to the fields on the associations between the built environment and pedestrian volume by simultaneously investigating both macro- and micro-scale built environment features. Second, collective walking behaviors are measured in terms of pedestrian volume for a larger geographic area (i.e., the entire urban area of Shanghai) than in previous studies, which enables our investigation with a large representative sample. Third, we focus on a dense Chinese city undergoing rapid urbanization, which is relatively less studied in the literature. Our findings can serve as guidelines for policymakers and urban planners to incorporate health promotion into built environment interventions.

1.1. Literature review

1.1.1. Assessing population-level walking behavior

Although numerous studies have focused on individual-level walking behaviors, scant attention has been paid to population-level walking behaviors on a large scale because of the difficulty of collecting such data (Cesare et al., 2019;Foster et al., 2018 ; Hankey et al., 2017 ; Im & Choi, 2018). Individual-level walking behaviors are typically collected via surveys and questionnaires (Ewing & Cervero, 2010; Saelens & Handy, 2008). To enquire whether an individual has achieved the recommended level of physical activity, researchers usually focus on the individual's duration and frequency of individual-level walking trips (Bornioli et al., 2019; Christman et al., 2019; Lu, Sarkar, & Xiao, 2018). However, the precise geographical contexts of individual walking trips are largely unknown, making it difficult to granularly identify built environment factors that affect individual-level walking behaviors, namely, the bias of the uncertain geographic context problem (Kelly et al., 2014; Kwan, 2012; Saelens & Handy, 2008).

Recently, some scholars have argued that more attention should be paid to population-level walking behaviors, because such behaviors can reflect the overall intensity of physical activity in a large population (Foster et al., 2018; Hankey et al., 2017; Im & Choi, 2018). Furthermore, population-level walking behaviors are directly affected by urban planning and urban design characteristics and hence are an easily modifiable outcome of potential urban planning interventions (Cesare et al., 2019). Recent studies indicate that pedestrian volume is a suitable proxy for population-level walking behaviors (Cambra & Moura, 2020; Hankey et al., 2017; Kang, 2018). Two approaches are typically used to assess pedestrian volume. One approach is to aggregate individual walking data into a certain geographic unit (e.g., a community block) (Boer et al., 2007; Sung et al., 2015). For instance, a study conducted in South Korea aggregated a relatively large individual-level survey dataset at the administrative block level to assess population-level walking trips (Sung et al., 2015). Nonetheless, studies have evaluated walking and built environment characteristics within certain spatial boundaries (e.g., residential neighborhood; community), which can cause the modifiable areal unit problem (MAUP) (Wong, 2004). The other approach is to conduct a field audit to count the number of pedestrians on different street segments (Brownson et al., 2009; Cambra & Moura, 2020; Hajrasouliha & Yin, 2015; Kang, 2018; Kelly et al., 2014). For instance, Hankey et al. (2017) estimated block-level pedestrian volume based on field observation data to represent population-level rates of active travel.

However, both these approaches have certain limitations. Specifically, surveys require respondents to recall their walking behaviors over a week or month, which may cause recall bias. Field audits require many investigators to record pedestrian walking behaviors for a long time, which is expensive and labor-intensive (Cambra & Moura, 2020; Chen et al., 2020; Kelly et al., 2014; Yin et al., 2015). It is difficult to measure and estimate pedestrian volume at a large spatial scale.

1.1.2. Association between the built environment and walking behavior

There is strong evidence that various built environment characteristics affect walking behaviors (Saelens & Handy, 2008; Sallis et al., 2012). The features of built environment can be divided into neighborhood-level macro-scale features (e.g., urban density, land use, street connectivity) and street-level micro-scale features (e.g., street tree, sidewalk) (Ewing et al., 2016; Nagata et al., 2020).

The features of the macro-scale built environment can be operationalized as five D variables: density, diversity, design, destination accessibility, and distance to transit (i.e., the 5Ds framework) (Boer et al., 2007; Ewing & Cervero, 2010; Kang, 2018; Lu, Chen, et al., 2018). Overall, people tend to walk more in an environment with higher levels of density, diversity, and destination accessibility, better pedestrian-oriented design, and shorter distance to transit (Cerin et al., 2007; Hajrasouliha & Yin, 2015; Saelens & Handy, 2008). However, there are mixed findings of which aspects of the macro-scale built environment affecting walking within distinctive urban contexts (Barnett et al., 2017; Forsyth et al., 2007; Kang, 2018).

Micro-scale built environment characteristics mainly refer to the elements and features that pedestrians can directly perceive on the streets (Boarnet et al., 2011; Ewing et al., 2016; Nagata et al., 2020). Streetscape features, such as characteristics of building (Boarnet et al., 2011), open sky (Yin & Wang, 2016), greenspaces (Lu, Sarkar, & Xiao, 2018), and sidewalk (Nagata et al., 2020), have been associated with walking behaviors. Nevertheless, the built environment characteristics were typically measured by either macro-scale D variables (Boer et al., 2007; Cerin et al., 2007; Lu et al., 2017) or micro-scale streetscape features (Boarnet et al., 2011; Hajrasouliha & Yin, 2015). Few studies have simultaneously evaluated both in a large geographic area.

1.1.3. Auditing the built environment and pedestrian volume using street view images

In light of the increasing availability of street view images, researchers have developed desk-based audit tools to assess micro-scale built environment characteristics (Badland et al., 2010;Rundle et al., 2011 ; Rzotkiewicz et al., 2018). This new approach tends to produce reliable results compared with field audit, due to the extensive data availability and highly consistent image characteristics (Rundle et al., 2011; Rzotkiewicz et al., 2018). For instance, study reported that street view data provides a valid measure for nine categories of street characteristics (e.g., pavement width, and obstruction) (Griew et al., 2013). However, desk-based environment audit tool remains time-consuming. Recently, researchers have integrated street view images with machine learning to assess various aspects of streetscape features (Biljecki

& Ito, 2021; Kang et al., 2020), for example, the presence of street greenery (Li et al., 2015; Lu, Sarkar, & Xiao, 2018; Xia et al., 2021), street tree (Lumnitz et al., 2021; Richards & Edwards, 2017; Seiferling et al., 2017), open sky (Yin & Wang, 2016), building characteristics (Gong et al., 2018; Gonzalez et al., 2020; Kang et al., 2018), sidewalk (Nagata et al., 2020; Ning et al., 2021), perception of place (e.g., safety, lively, aesthetics, and depressing) (Kruse et al., 2021; Ma et al., 2021; Verma et al., 2020; Zhang et al., 2018), housing price (Law et al., 2019), and neighborhood demographics (Gebru et al., 2017). Machine learning-based approach is able to capture micro-scale urban environment with a larger geographic reach and higher efficiency.

Furthermore, researchers have recently used street view images (e.g., Google Street View or Baidu Street View images) to estimate pedestrian volume because image-based pedestrian detection techniques can automatically count pedestrians with high accuracy (Chen et al., 2020; Yin et al., 2015). For example, street view images integrated with machine learning algorithm has been validated with high reliability to estimate pedestrian volume at street level compared with field audits (Chen et al., 2020). Therefore, the combination of street view images and machine learning is a promising approach for efficiently and accurately assessing population-level walking behaviors.

To the best of our knowledge, no study has detected citywide pedestrian volume using street view images and associated it with both macro- and micro-scale built environment characteristics. Hence, little is known about the associations of citywide pedestrian volume and built environment characteristics, especially under a high-density urban context.

2. Data and methods

2.1. Research area

Shanghai is a large metropolis with a population of about 24.3 million in 2019 and serves as the economic, financial, industrial, and transportation hub of China. This study was conducted in the Middle Ring Road area (approximately 315 km^2) of Shanghai (Fig. 1), roughly covering the most populous and urbanized area of the city.

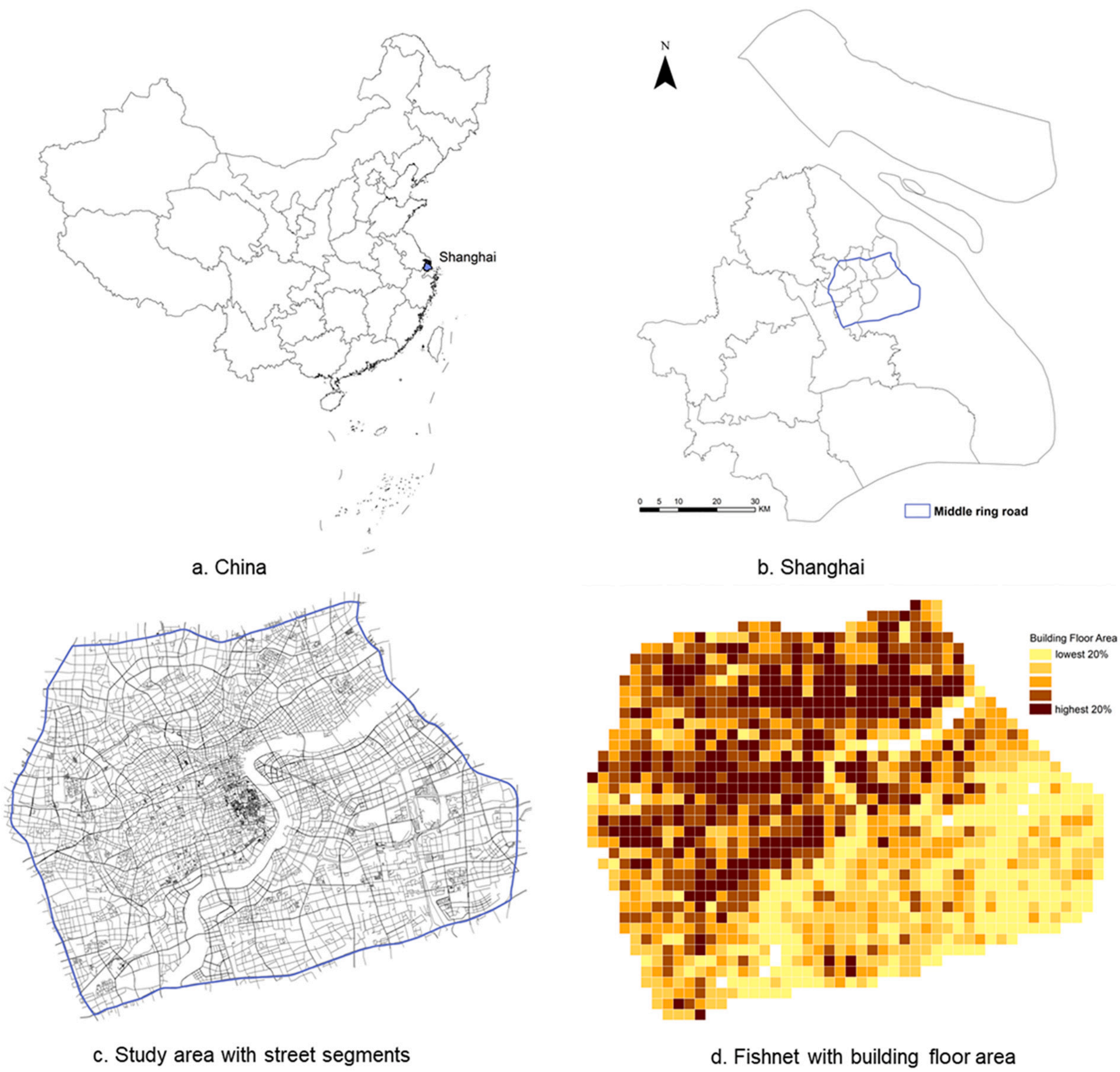


Fig. 1. Study area: a) map of China; b) map of Shanghai; c) study area showing street segments; d) study area divided into 500 m × 500 m fishnet showing building floor area.

2.2. Outcome variable: pedestrian volume

In this study, pedestrian volume, estimated from street view images collected from Baidu Map (https://map.baidu.com), was used as the proxy for population-level walking behaviors. To improve the representation of spatial features, the images were collected every 30 m along all streets in the study area. Accordingly, images were collected from 127,921 sampling points along 28,397 street segments totaling 3,393 km in length. According to data availability, nearly all of the street view images were collected with a timestamp of 2017 in Baidu Street View to match the data collection time period of the built environment factors (e.g., point of interest data). Street view collection vehicles for Baidu Map generally collect street view along streets with a bright and warm weather.

Existing studies have thoroughly demonstrated that street view images can estimate pedestrian volume at street level combined with machine learning (Chen et al., 2020; Yin et al., 2015). By setting proper image retrieving parameters (e.g., heading, pitch, field of view), street frontage on both sides can be captured in images to automatically count pedestrians. To estimate the pedestrian volume, at each sampling point, we sampled two street view images at headings of 90° and 270° (i.e., capturing street frontage on both sides of the street) and a pitch (vertical direction), field of view, pixel size, and quality parameter of 0°, 90°, 1024 × 1024 pixels, and 100, respectively. Then, the images were cropped from 312 to 712 at their vertical axes to a size of 1024 × 400 pixels which mainly cover the sidewalk range of the street. Thereafter, the crowd counting feature of Baidu AI (https://ai.baidu.com/tech/body/num) through its application programming interface (API) was used to count the pedestrians in the images. Machine learning interface provided by AI company is able to achieve state-of-the-art accuracy and high computational capacity in pedestrian detection. In a pilot test on 50 randomly selected images, Baidu AI has highly agreement with expert judgement (Pearson's $r = 0.94$).

A 500 m × 500 m fishnet with 1322 grids was generated over the study area; these grids served as both spatial units and analysis units. The pedestrian volume in a grid was then measured as the average number of pedestrians in each image sampled within that grid.

2.3. Micro-scale built environment characteristics

In this study, micro-scale built environment characteristics refer to streetscape features that pedestrians can directly perceive. Recently, numerous studies have been conducted to audit street-level built environment features using street view images and machine learning (Ma et al., 2021; Nagata et al., 2020; Zhang et al., 2018). The micro-scale characteristics were extracted from the street view images by using PSPNet (Zhao et al., 2017), an effective machine learning algorithm for scene parsing and semantic segmentation via the pyramid pooling module and the pyramid scene parsing network. This approach has achieved state-of-the-art pixel-level prediction performance on various datasets, such as Cityscapes (Zhao et al., 2017). By using a pre-trained Cityscapes model, each street view image was segmented into 19 categories of ground objects. For each ground object, we calculated the ratio of the number of pixels representing the object to the total number of pixels in the image. We chose greenery, open sky, building, roadway (i.e., street width), and sidewalk to represent the micro-scale built environment, as the presence of these elements have been associated with walking behaviors (Ewing et al., 2016; Nagata et al., 2020). At each sampling point, this ratio of streetscape features was evaluated in two images - one each facing the front (0°) and back (180°) of the street (Fig. 2) - to more comprehensively match pedestrians' perception. The micro-scale streetscape features in a grid were then measured as the average ratios of sampling points within that grid for greenery, open sky, building, roadway, and sidewalk respectively.

2.4. Macro-scale built environment characteristics

Macro-scale built environment indicators were selected based on the 5Ds framework: density, diversity, design, destination accessibility, and distance to transit (Ewing & Cervero, 2010; Kang, 2018; Lu, Chen, et al., 2018). Density was measured in terms of building floor area in each grid. To measure diversity, we used point of interest (POI) data, a fine-grained data source providing comprehensive and accurate information on urban land use. The POI dataset was retrieved from Gaode Map, one of the most popular online map services in China, via its API (https://lbs.amap.com/). POIs in the Gaode Map database are divided into more than twenty categories. For this study, we reclassified the original POI dataset into five categories, namely, residential, enterprise, commercial, public service, and entertainment (Table 1), representing the five fundamental functions of a city (Zhao et al., 2020). After removing irrelevant and duplicate entries, we obtained 465,144 effective POI entities. Diversity was calculated on the basis of the entropy score (Eq. 1) of these POI data in each grid (Shannon, 1948).

$$\text{Mix index} = -\sum_{i=1}^{n} p_i ln p_i \tag{1}$$

where p_i represents the proportion of ith of POI type, and n is the total number of POI types presented in that grid.

Design was operationalized in terms of the number of street intersections and street centrality in each grid. Street centrality represents the accessibility of a street segment in the street network, measured through spatial design network analysis (sDNA) as the betweenness value at a radius of 800 m (Cooper & Chiaradia, 2020). Destination accessibility was measured in terms of the number of POIs for the five fundamental POI types respectively in each grid. Finally, distance to transit was evaluated as the number of transit stops, including subway and bus stops in each grid.

2.5. Statistical analysis

Before the statistical analysis, we tested collinearity among the independent variables (Table 2) using the variance inflation factor (VIF). All of the variables had a VIF of ≤4 except for the proportion of building in the street view data, which was hence excluded from the follow-up analysis.

First, we used ordinary least square (OLS) regression to investigate the relationships between the built environment and the pedestrian volume. OLS holds the basic assumption that the residual is random and homoscedastic (Anselin & Rey, 1991). The OLS model can be described as follows:

$$y = X\beta + \varepsilon \tag{2}$$

where y is the dependent variable, X is the matrix of the explanatory variables, β is a vector of the coefficients, and ε is a vector of random error terms.

The results (e.g., coefficient size, significance) of the OLS model could be biased if spatial effects exist. Spatial data usually has the spatial dependence problem: that is, a value observed in one location depends on the values observed in neighboring locations. Therefore, we also used the spatial lag model (SLM) and the spatial error model (SEM) (Anselin & Rey, 1991). SLM posits that spatial dependence could be a result of autocorrelation in the dependent variable, whereas SEM tends to consider autocorrelation in the error term (Anselin & Rey, 1991). We firstly conducted OLS model in Geoda (Anselin et al., 2010) to determine which spatial model is more appropriate. Lagrange Multiplier (LM) and robust LM of diagnostics are often used to identify the fitness of spatial models. The results showed that SLM has a higher value of LM (312.63 of SLM vs. 252.31 of SEM) and Robust LM (70.84 of SLM vs. 10.52 of SEM) than does SEM, indicating that SLM is more appropriate. Moreover, we found that the spatial dependence of pedestrian volume is significant

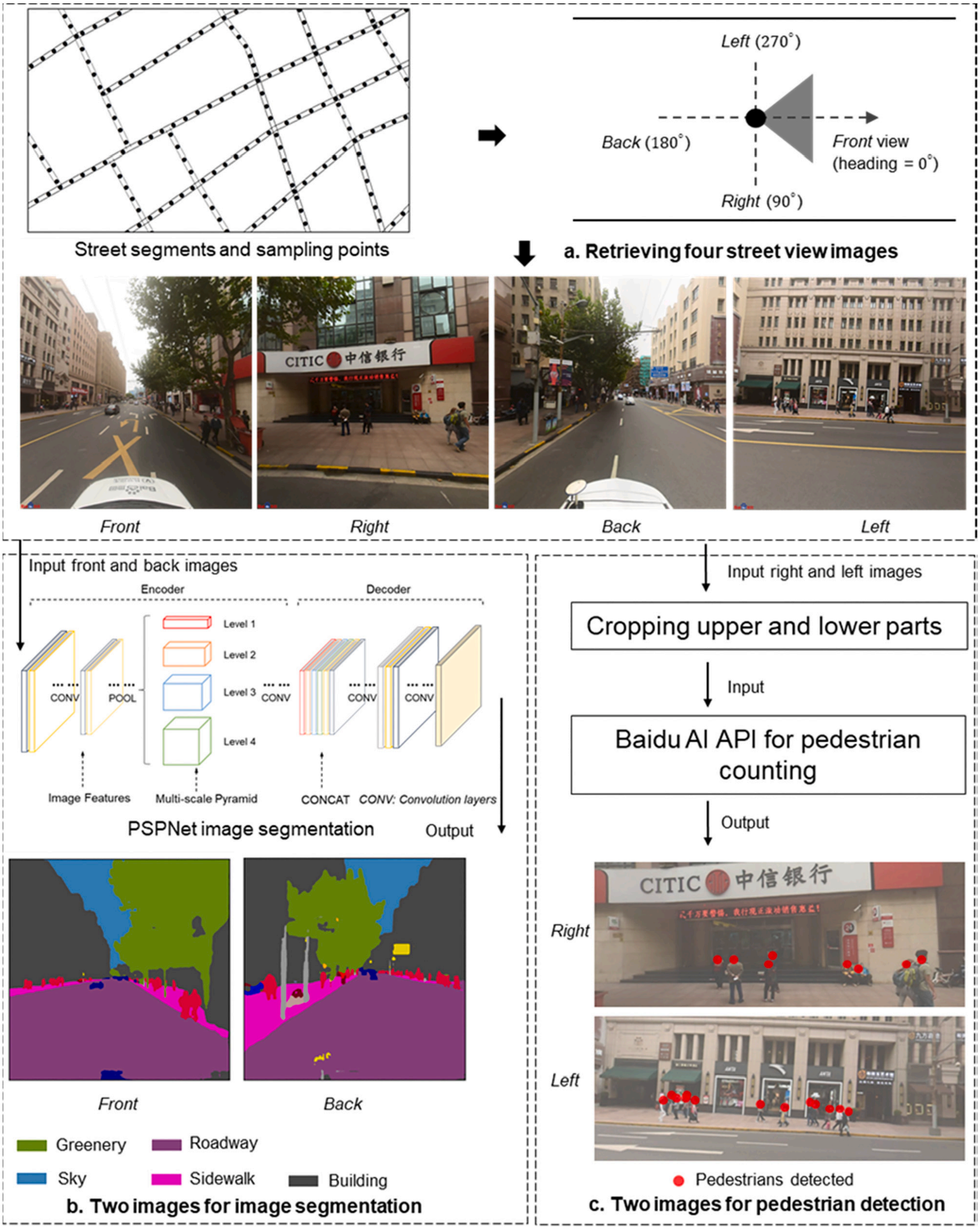


Fig. 2. Assessing pedestrian volume and streetscape features from street view images: a) at each sampling point, four street view images were retrieved; b) front (0°) and back (180°) views were used for segmentation; c) right (90°) and left (270°) views were used for assessing pedestrian volume.

Table 1
Five fundamental POI types in this study and the corresponding categories in the original Gaode Map dataset.

POI types	Categories in the Gaode map dataset	Count	Percentage
Residential	Commercial house, residential building, residential community	22,731	4.89%
Enterprise	Enterprise, company, factory	113,286	24.36%
Commercial	Food, beverage, shopping mall, market, store, theatre, commercial service office	283,944	61.04%
Public service	Hospital, school, governmental organization, social group, management institution	26,633	5.73%
Entertainment	Scenic spot, park, open square, tourist attraction	18,550	3.98%

Table 2
Summary statistics for all variables within the Middle Ring Road area in Shanghai, sampled in 2017 (Fishnet = 500 m × 500 m, $N = 1322$).

Variables (Unit)	Min.	Max.	Mean	SD
Dependent variable				
Pedestrian volume (N)	0	31.278	5.280	4.827
Independent variables				
Micro-scale built environment				
Greenery (0–1)	0	0.458	0.173	0.076
Open sky (0–1)	0.005	0.383	0.192	0.072
Building (0–1)	0.017	0.492	0.185	0.076
Roadway (0–1)	0.167	0.617	0.351	0.038
Sidewalk (0–1)	0	0.061	0.016	0.008
Macro-scale built environment				
Building floor area (m^2)	0	1,674,069	359,748	192,454
Land-use mix index (≥0)	0	1.591	0.981	0.305
Street intersection (N)	0	119	34.170	18.764
Street centrality (≥0)	0	21,648	510.400	1379.543
Residential POIs (N)	0	159	16.890	16.730
Enterprise POIs (N)	0	1420	84.580	135.313
Commercial POIs (N)	0	3503	211.400	308.797
Public service POIs (N)	0	251	19.710	21.751
Entertainment POIs (N)	0	313	13.770	18.342
Transit stops (N)	0	19	2.756	2.828

Note: Min. = Minimum; Max. = Maximum; SD = Standard deviation; N = Number.

(Moran's $I = 0.41$; $p < 0.001$). SLM can be expressed as follows:

$$y = \rho W_y + X\beta + \varepsilon \tag{3}$$

where ρ is a spatial autocorrelation parameter, and W_y is a spatial weight matrix of the spatial lags for the dependent variables at nearby locations. With the cell of the fishnet (i.e., the fishnet grid) as the basic spatial unit in the analysis, queen contiguity was used to generate the spatial weights. The spatial regression models were run in GeoDa software. We believe that SLM can minimize the spatial effects, and that OLS and SLM analyses prove the robustness of the relationships. Notably, in our final regression analysis, the dependent variable of pedestrian volume was converted with a natural logarithmic transformation to achieve a better normal distribution and meet the assumption of regression.

3. Results

The descriptive statistics of the pedestrian volume and built environment factors are presented in Table 2. The average pedestrian volume for all grid was 5.28 persons, indicating there are 5.28 persons in each street view image in a grid. Regarding the micro-scale built environment, the average ratios of streetscape greenery, open sky, roadway, and sidewalk for all grids were 0.17 (standard deviation (SD) = 0.08), 0.19 (SD = 0.07), 0.18 (SD = 0.08), 0.35 (SD = 0.04), and 0.02 (SD = 0.01), respectively. Regarding the macro-scale built environment, the mean value of all grids for building floor area was 359,748 m^2 (SD = 192,454). The average value of all grids for land-use mix was 0.98 (SD = 0.30). The average number of street intersections was 34.17 (SD = 18.76), while the average betweenness for street centrality was 510.40 (SD = 1379.54). The average number of residential, enterprise, commercial, public service, and entertainment POIs were 16.890 (SD = 16.73), 84.580 (SD = 135.31), 211.40 (SD = 308.80), 19.71 (SD = 21.75), and 13.77 (SD = 18.34), respectively. The average number of transit stops was 2.76 (SD = 2.83).

Fig. 3 shows the mean pedestrian volume in each street segment and fishnet grid. Pedestrian volume is varied in different street segments and grids across our study area.

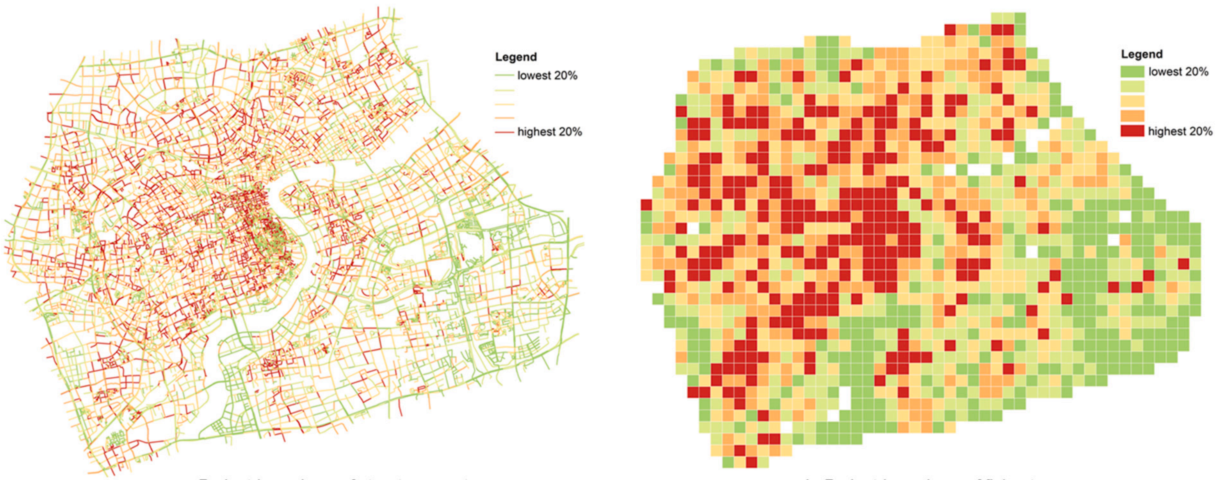
Table 3 presents the associations between the built environment and the pedestrian volume. SLM outperformed OLS in terms of goodness-of-fit (R^2, log-likelihood, and AIC), so we mainly focus on the SLM results herein. Regarding the micro-scale built environment, streetscape greenery, open sky, and sidewalk were positively associated with pedestrian volume. Regarding the macro-scale built environment, building floor area was positively associated with pedestrian volume. Regarding diversity, the land-use mix index and number of street intersections were positively associated with pedestrian volume. Destination accessibility exhibited significant associations with pedestrian volume. The number of commercial POIs and public service POIs were positively associated with pedestrian volume, while the number of enterprise POIs was negatively associated with pedestrian volume. Furthermore, the number of transit stops was positively associated with pedestrian volume. Hierarchical regression showed that the micro-scale built environment independently achieved an R^2 of 0.51 (0.17 of OLS), while R^2 reached 0.60 (0.49 of OLS) when both the micro- and macro-scale built environment were considered in the models. In addition, scattering plots using 2D histogram (see Appendix) were provided for measurements of pedestrian volume and predictions of pedestrian volume using OLS model, and measurements of pedestrian volume and measurements of the significant built environment factors using the regression dataset.

4. Discussion

This work extends previous research on the association between the built environment and walking behaviors in several respects. First, it makes a novel methodological contribution to assess population-level pedestrian volume using street view images and machine learning technique. The proposed method is superior to previous methods (such as surveys and field audits) in terms of efficiency and geographic reach, making it feasible to collect population-level waking behaviors for an entire city or for multiple cities within a short period. Therefore, the proposed method can help advance research on healthy cities, walkability, urban planning, and other related topics.

Second, the proposed method can simultaneously examine the effects of the micro- and macro-scale built environment on pedestrian volume and can thus more comprehensively clarify the effects of built environment characteristics on walking behaviors. Third, the present study systematically explored built environment and walking behaviors in a dense Chinese metropolis, which is relatively less studied in the literature, as most studies have been conducted in low- or medium-density cities in developed countries.

The present study yielded three major findings. First, we found that some macro-scale built environment characteristics in the 5Ds framework are associated with pedestrian volume, which is largely consistent with the findings of previous studies. Specifically, (1) urban density, measured in terms of building floor area, is positively associated with pedestrian volume. Building floor area can reflect the potential supply of pedestrians, as a larger floor area can accommodate more people for various activities. That high levels of population density, building density, or building floor area can stimulate walking at either the individual or population level has also been reported previously (Forsyth et al., 2007; Kang, 2018). (2) Diversity is positively correlated with pedestrian



a. Pedestrian volume of street segments

b. Pedestrian volume of fishnet

Fig. 3. Pedestrian volume estimated from street view images: mean pedestrian volume in a) each street segment, and b) fishnet grid.

Table 3
Results of regression models for predicting pedestrian volume (Fishnet = 500 m × 500 m, $N = 1322$).

Model predictors	OLS		SLM	
	Coef. (SE)	*p*-Value	Coef. (SE)	*p*-Value
Micro-scale built environment				
Greenery	1.306 (0.515)	0.010*	1.156 (0.456)	0.011*
Open sky	1.573 (0.637)	0.013*	2.231 (0.567)	<0.001***
Roadway	0.355 (0.900)	0.675	0.872 (0.798)	0.275
Sidewalk	17.735 (4.130)	<0.001***	11.056 (3.701)	0.003**
Macro-scale built environment				
Building floor area	0.001 (0.000)	<0.001***	0.001 (0.000)	<0.001***
Mix index	1.047 (0.112)	<0.001***	0.733 (0.100)	<0.001***
Street intersection	0.010 (0.002)	<0.001***	0.006 (0.002)	<0.001***
Street centrality	0.001 (0.000)	0.011*	0.001 (0.000)	0.076
Residential POIs	0.004 (0.003)	0.120	0.002 (0.002)	0.507
Enterprise POIs	−0.001 (0.000)	0.005**	−0.001 (0.000)	0.012*
Commercial POIs	0.001 (0.000)	<0.001***	0.001 (0.000)	<0.001***
Public service POIs	0.006 (0.002)	0.003**	0.003 (0.002)	0.049*
Entertainment POIs	−0.003 (0.002)	0.131	−0.002 (0.002)	0.373
Transit stops	0.088 (0.012)	<0.001***	0.072 (0.011)	<0.001***
Micro R^2	0.167		0.506	
Micro and Macro R^2	0.493		0.597	
LL	−1955		−1831	
AIC	3939		3694	

Note: Coef. = Coefficient; SE = Standard error; LL = Log-likelihood; AIC = Akaike information criterion.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

volume. Places with various land use types provide a diverse set of destinations for people to walk to, so higher land use diversity can promote pedestrian volume (Cerin et al., 2007; Im & Choi, 2018). (3) Street network design, which is measured in terms of street intersection density and betweenness centrality via graph theory, is positively associated with pedestrian volume. A better connected street network makes more destinations available within walking distance, further encouraging walking behaviors (Hajrasouliha & Yin, 2015). (4) Pedestrian destination accessibility, measured using POI data, is positively linked to pedestrian volume. In particular, the density of commercial and public service POIs has a positive effect on pedestrian volume. Previous findings support that greater choice of commercial and service destinations can better stimulate walking behaviors (Hahm et al., 2017). However, the density of enterprise POIs is negatively associated with pedestrian volume. This is because places with a high concentration of enterprise POIs are more likely to be the major workplaces within a city (Li et al., 2018). In addition, given that the average commute distance and duration is relatively long in Shanghai, people may prefer cars or public transportation modes over walking for their commutes, resulting in low pedestrian volumes (Li et al., 2018). (5) A shorter distance to transit may encourage walking behaviors, as people often walk to and from major transit stations while taking public transport (Cerin et al., 2007; Kang, 2018).

Second, we found that some micro-scale streetscape features play a vital role in influencing population-level waking behaviors. Specifically, street-level greenery, sidewalk, and open sky are all positively associated with pedestrian volume. Pedestrians are more likely to walk on streets with more visible greenery, as greenery can improve pedestrians' walking experience by increasing shade (Hahm et al., 2017) and reducing stress (Wang, Yang, et al., 2020); this finding is consistent with those from other cities (Lu, Sarkar, & Xiao, 2018). In addition, the presence of wide sidewalks, as a major walking infrastructure, can create a safe and pleasant walking environment and hence promote walking behaviors (Day, 2016; Nagata et al., 2020; Saelens & Handy, 2008). Furthermore, we found that the level of open sky is positively associated with pedestrian volume, which is inconsistent with the finding of a previous study (Yin & Wang, 2016). The different urban contexts in the two studies may explain this inconsistency. Our research was conducted in Shanghai, China, a dense urban area, whereas (Yin & Wang, 2016) was conducted in Buffalo, New York, USA, a city with relatively low urban density. Hence, the level of open sky in Shanghai is much lower than that in Buffalo. In high-density cities, more open sky and daylighting may promote walking behaviors. However, in low-density or medium-density cities, more open sky may make the street too sunny and hot to walk on. This indicates that the association between open sky and pedestrian volume may be context-sensitive. Additional studies are warranted to investigate the complex effect of open sky on walking behaviors.

Third, we found that both micro- and macro-scale built environment variables have independent effects on pedestrian volume. Built environment characteristics related to walking behaviors have been defined and measured differently by different researchers (Barnett et al., 2017; Day, 2016; Saelens & Handy, 2008). Conceptually, macro-scale built environment characteristics are largely related to proximity to potential pedestrian destinations. For example, a higher urban density, a more diverse land use mix, better connected streets, and more POIs all make potential pedestrian destinations closer and more accessible by walking. By comparison, micro-scale built environment characteristics relate to the qualities of the walking environment (e.g., aesthetics and safety). Our results suggest that wider sidewalks, more street-level vegetation along the streets, and higher levels of open sky can create a pleasant and safe walking environment and stimulate walking. Overall, pedestrian volume is linked with both the macro-scale built environment characteristics and micro-scale streetscape features.

4.1. Policy implications

Walking is arguably the most popular and feasible form of physical activity for the vast majority of the population (Eyler et al., 2003; Lee & Buchner, 2008). Urban residents can relatively easily integrate walking into their daily lives for various purposes, for example, transportation, recreation, and exercise. Promoting collective walking behavior is the key to improve urban vitality, and it also engenders many social, economic, and environmental benefits (Lee et al., 2012; Sallis et al., 2012). According to our major findings with an urban context in Shanghai, China, relatively dense and diverse urban development may boost pedestrian volume. Well-connected street network design (i.e., intersections and centrality) is crucial for pedestrian activity. Urban areas with more transit stops also tend to have more pedestrians. In regard to accessibility of destinations, urban areas with more commercial and public service destinations can stimulate street-level walking behaviors. Urban design strategies, such as providing more greenery, openness and sidewalk at street level, are also important to increase pedestrian volume. Therefore, urban planners and designers should make efforts to create pedestrian-oriented urban environment that have abundant destinations (e.g., commercial, and public service), mixed use, well-connected street network, and adequate greenery, openness, and sidewalk at street level. In summary, policymakers and practitioners should consider both the macro- and micro-scale characteristics of the built environment to create pedestrian-friendly and healthy cities at population level.

However, some caveats should be noticed. Urban area with more enterprises is linked with fewer pedestrians, and residential destinations and entertainment spots (i.e., open space, parks) are not linked to pedestrian volume in Shanghai. However, different findings were reported; higher residential density is linked to walking (Forsyth et al., 2007), so are parks and open space (Giles-Corti et al., 2005; Zhai et al., 2021). The inconsistency in the findings may be due to different urban contexts. It may be ineffective to stimulate pedestrian volume by increasing residential destinations and enterprises in the major cities in China. Furthermore, it is street-level greenery and openness rather public open space and parks that play important roles to stimulate street-level walking behaviors.

4.2. Limitations

The following limitations need to be noted. First, although pedestrian volume was automatically extracted at the street level, we aggregated and averaged the data for 500 m × 500 m grids. In addition, other street-level factors are also measured and averaged for each grid. To some extent, aggregating pedestrian volume at the grid level will lead to ecological fallacy and loss of information (Kwan, 2018). Nevertheless, we used the fishnet grid rather than individual street segments as the unit of analysis because macro-scale built environment characteristics are difficult to assign to individual streets.

Second, street view images were collected at different hours (e.g., peak hours vs. non-peak hours) and different days in a week (e.g., weekday vs. weekend) which is able to impact pedestrian volume. Because of data attributes of Baidu Street View, we are currently unable to handle the potential temporal fluctuation of pedestrian volumes in these images. Third, only a few aspects of street quality were considered. However, other walking-influencing aspects of street quality (e.g., comfort, safety, aesthetics) were not explored in the current study. Additional studies are needed to explore the effects of other aspects of street quality on walking behavior (Bornioli et al., 2019; Zhang et al., 2018).

Fourth, personal factors (e.g., age, income), which significantly influence walking, were not examined (Adkins et al., 2017; Barnett et al., 2017; Kerr et al., 2007). Finally, as this was a cross-sectional study, no causality can be established. Longitudinal or natural experiment studies are needed to obtain more rigorous evidence of the effect of built environment characteristics on pedestrian volume.

5. Conclusion

This study is the first to systematically explore the association between the built environment and pedestrian volume at a large spatial scale. Pedestrian volume was retrieved using an innovative method that integrates street view data with machine learning technique. Micro-scale built environment characteristics, such as greenery, open sky, and sidewalk, were found to be associated with pedestrian volume. Micro-scale built environment characteristics (i.e., the 5Ds framework: density, diversity, design, destination accessibility, and distance to transit) were also found to be associated with pedestrian volume. Thus, to improve walking behaviors through urban planning and design, policymakers should focus on both the micro- and macro-scale built environment.

CRediT authorship contribution statement

Long Chen: Methodology, Formal analysis, Visualization, Writing-Original Draft, Data Collection. Yi Lu: Conceptualization, Writing-Reviewing and Editing, Validation, Supervision. Yu Ye: Writing-Reviewing and Editing, Data Collection. Yang Xiao: Writing-Reviewing and Editing. Linchuan Yang: Writing-Reviewing and Editing.

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Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2022.103734.

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