Transportation Research Part D 101 (2021) 103096

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Spatial disparity of individual and collective walking behaviors: A new theoretical framework

Yuxiao Jiang [a,b], Long Chen [a], George Grekousis [c,d], Yang Xiao [e], Yu Ye [f], Yi Lu [a,g,*]

[a] Department of Architecture and Civil Engineering, City University of Hong Kong, Hong Kong
[b] School of Architecture, Tianjin University, Tianjin, China
[c] School of Geography and Planning, Department of Urban and Regional Planning, Sun Yat-Sen University, Guangzhou, China
[d] Guangdong Key Laboratory for Urbanization and Geo-simulation, Sun Yat-sen University, Guangzhou, China
[e] Department of Urban Planning, Tongji University, Shanghai, China
[f] Department of Architecture, Tongji University, Shanghai, China
[g] City University of Hong Kong Shenzhen Research Institute, Shenzhen, China

ARTICLE INFO

Keywords:
Walkability
Walking
Built environment
Machine learning
Spatial disparity
Street view images

ABSTRACT

The creation of walkable environments, and the promotion of walkability for health and environmental benefits have been widely advocated. However, the term "walkability" is often associated with two related but distinct walking behaviors: individual and collective walking behaviors. It is unclear whether spatial disparity exists between them, and whether built environment characteristics have distinctive effects on them.

This research was the first to explore the spatial disparity between the two types of walking behaviors. Collective walking behaviors were measured using the citywide pedestrian volume, extracted from 219,248 street view images. Individual walking behaviors were measured form a population-level survey. Spatial mismatches were found between the two types of walking behaviors and built environment elements had stronger associations with collective walking behaviors. Therefore, it is prudent to theoretically differentiate collective and individual walking behaviors, and targeted planning policies must be developed to promote one or both types of walking behaviors.

1. Introduction

1.1. Importance of walking and walkability

In recent years, the building of more walkable environments and the improvement of walkability in urban areas have become active research areas in several fields, including public health, urban planning, transportation, and sociology.

Increases in regular walking activities at the personal level are beneficial for physical and mental health of individual residents. Moreover, as walking is the most accessible form of exercise and is the least prone to injury, walking is suitable for people of both genders and all ages, races, and economic conditions (Litman, 2003). Many studies have proved that walking increases public health (Lee & Buchner, 2008), especially in terms of weight control (Sallis, Floyd, Rodríguez, & Saelens, 2012) and the prevention of

* Corresponding author at: Department of Architecture and Civil Engineering, City University of Hong Kong, Hong Kong.
E-mail addresses: yuxijiang8-c@my.cityu.edu.hk (Y. Jiang), lochen6-c@my.cityu.edu.hk (L. Chen), graikousis@mail.sysu.edu.cn (G. Grekousis), yxiao@tongji.edu.cn (Y. Xiao), yye@tongji.edu.cn (Y. Ye), yilu24@cityu.edu.hk (Y. Lu).

https://doi.org/10.1016/j.trd.2021.103096

Available online 17 November 2021
1361-9209/

cardiovascular diseases (Murtagh et al., 2015) and other chronic diseases (Booth, Roberts, & Laye, 2011). Additionally, walking plays an important role in mental health (Kelly et al., 2018), as it can increase environmental perception (Sugiyama, Leslie, Giles-Corti, & Owen, 2008) and social activities (Wood, Frank, & Giles-Corti, 2010).

Furthermore, abundant pedestrian behaviors on streets have additional benefits for the whole society. For example, they can help to reduce carbon emissions (Neves & Brand, 2019), promote social interaction (Gehl, 2013), increase social cohesion (Talen, 1999), and enhance urban vitality (Sung & Lee, 2015). From the perspective of urban planning, street walking activity is considered as a core indicator in the measurement of urban vitality (Jacobs, 1965). The presence of pedestrian increases the attractiveness of an urban area (Gehl, 2013). Moreover, walking, as a primary and the most inclusive transportation mode, can help residents of different socio-economic status reach varying urban spaces; hence, walkable urban environment promotes social equity (Middleton, 2018).

1.2. Two types of walkability and walking behaviors

The term "walkability" remains vaguely defined, and its meaning may differ for different researchers or different design practitioners (Lo, 2009; Moura, Cambra, & Gonçalves, 2017).

First, some researchers have suggested that walkability is a measure of the urban design conditions that promote the walking behaviors of individuals for transportation or recreational purposes (Forsyth, 2015); hence, increased walkability can improve traffic conditions and the health of individuals. In the current study, walkability related to individual walking behaviors is referred to as *individual walkability*. Walking was first mentioned theoretically in the garden city model, as the primary transportation mode to connect residents, urban service facilities, and industrial areas (Howard, 1965). With the rapid development of automobiles, motor vehicles have become the dominant transportation mode in urban areas, which has triggered a series of urban problems (Couch, Petschel-Held, & Leontidou, 2008). New urbanism advocates building pedestrian communities by mixed land-use and by designing traffic-oriented communities, to relieve traffic congestion and environmental pollution (Calthorpe, 1993). Several urban-planning theories, such as the smart growth theory (Geller, 2003), the eco-city theory (Kenworthy, 2006), and the compact city theory (Burton, 2000), hold that people should be encouraged to use public transportation and walk, to reduce private automobile usage. Since the World Health Organization proposed the concept of a "healthy city" (Ashton, Grey, & Barnard, 1986), a pedestrian-friendly environment and walkability have become key indicators of healthy city planning, and are gradually becoming active topics in the fields of urban planning and public health (Corburn, 2009).

Second, some other researchers have suggested theories that regard walkability as a measure of the vibrancy and sociability of an environment, as these often result from abundant pedestrian activities on streets (Cambra & Moura, 2020; Lee & Talen, 2014; Middleton, 2018). In such theories, the collective walking behavior (such as pedestrian volume) on streets and other public spaces, is one of the key indicators of walkability (Gehl, 2013; Lee, Sung, & Woo, 2018; Sung, Lee, & Cheon, 2015). Therefore, in this study, the second type of walkability is referred to as *collective walkability*, because it is related to the collective walking behaviors on streets. To address the issue of the sprawl and declined urban vitality of urban centers, researchers have suggested that a walkable environment can increase overall pedestrian activities and hence improve urban vitality and social interactions (Frumkin, 2004). Urban planners can promote pedestrian gathering by increasing open spaces (Jacobs, 1965), improving urban design imageability (Lynch, 1984), street quality (Ashihara, 1983), and public space (Gehl, 1987). Five urban design elements, namely human scale, complexity, imageability, transparency, and enclosure have been found to be the main indicators for measuring neighborhood walkability and street vitality (Ewing & Clemente, 2013). These elements have eased urban expansion to a certain extent and improved urban vitality.

It is vital to distinguish individual (e.g., individual walking time) and collective (e.g., pedestrian volume) walking behaviors. First, longer total walking time of the residents in a neighborhood, does not necessarily indicate higher pedestrian volume because of low population density in this area or because walking may occur outside this neighborhood. For instance, many residential communities in suburban areas may have higher individual walking time but lower pedestrian volume. Second, higher pedestrian volume in a neighborhood does not necessarily indicate longer total walking time of its residents, because most pedestrians may live outside this neighborhood, or just because of very high population density. For instance, an area with high concentration of commercial destinations may have this phenomenon. In sum, areas that promote individual walking behavior may not promote collective walking behaviors, and vice versa. Therefore, it is necessary to explore the spatial disparity between individual and collective walking behaviors.

Urban design characteristics may induce both individual and collective walking behaviors, though the effects vary in terms of magnitude of the effects, and significant factors. There is strong evidence that individual walking behaviors, such as total walking distance or walking time, is related to the neighborhood-level built environment (Saelens, Sallis, & Frank, 2016). These built environment features have been summarized in a five-dimensional (5D) framework: distance to transit, density, design, destination accessibility, and diversity (Ewing & Cervero, 2010b). In addition, people's subjective perceptions of built environment, such as traffic safety and crime prevention features (Knuiman et al., 2014), and its level of community aesthetics (Panter, Griffin, & Ogilvie, 2014), have also been proven to have a vital effect on individual walking behavior.

There has been relatively less research on the link between the built environment and collective walking behaviors (Kim, Sohn, & Choo, 2016; Yin, Cheng, Wang, & Shao, 2015). To date, researchers have reported that collective walking behaviors, e.g., pedestrian volume on different streets, are related to urban density (Lee, Yoo, & Seo, 2020), street connectivity (Hajrasouliha & Yin, 2015), the presence and quality of sidewalks (Hermida, Cordero, & Orellana, 2019), and the distance to metro stations (Kim et al., 2016). Moreover, a study from Lisbon finds that planning interventions, such as increasing green spaces and sidewalk facilities, improve pedestrian flow and pedestrian perception (Cambra & Moura, 2020). However, such studies have only focused on small-scale urban areas, such as several commercial areas, residential areas, and metro-station buffer zones. There has been no research on the city-scale effects of the built environment on collective walking behaviors.

1.3. Methods to assess walking behaviors

The lack of research attention on collective walking behaviors may be due to the difficulty of collecting data on collective walking behaviors. Individual walking behaviors, such as walking time, distance, and trips, are often measured using well-established and easily implemented methods, such as self-reports or surveys (Barnett et al., 2017), Global Positioning System data (Kang, Moudon, Hurvitz, Reichley, & Saelens, 2013), and accelerometers (Chaix et al., 2016). In contrast, collective walking behaviors, such as pedestrian volume or counts on streets, are often assessed via field observations or video recordings (Yin, 2017). However, field

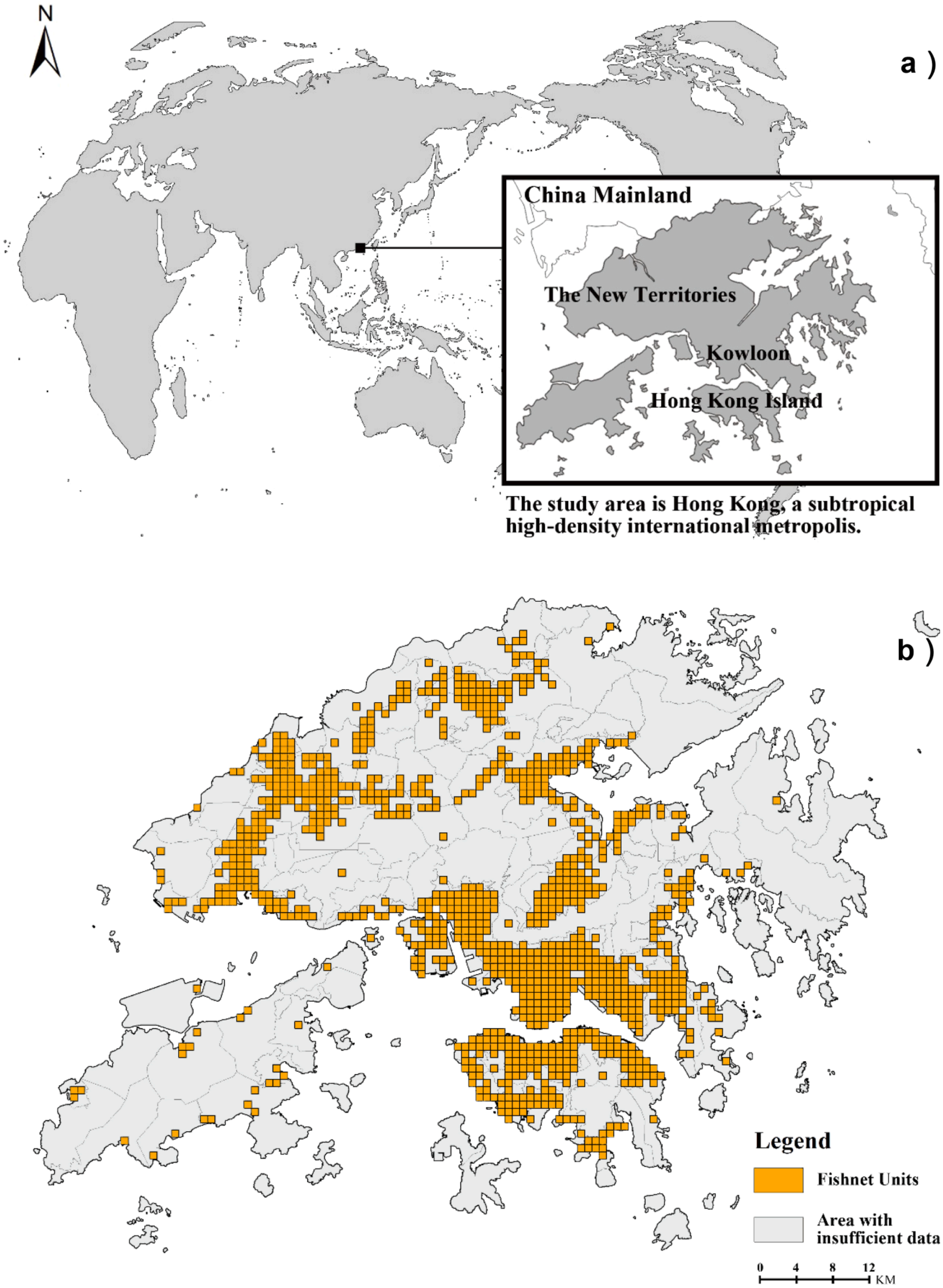

Fig. 1. a) Study area. b) Research area with a fishnet of 500 × 500 m rectangular grids.

observations are confined to small-scale study areas, due to their limitations of small sample sizes and low efficiency.

With the rapid development of urban big data, new research methods to assess collective walking behaviors have emerged. Some researchers have used mobile application (app) user location aggregate heatmaps (Zhang, Xiao, Luo, & Zhou, 2020), social media platforms (Steiger, Westerholt, Resch, & Zipf, 2015), or smart card data (Long & Thill, 2015) to assess pedestrian volumes for large-scale areas.

Recently, street view image (SVI) data have enabled new ways to assess pedestrian volumes (Rzotkiewicz, Pearson, Dougherty, Shortridge, & Wilson, 2018), as SVI data, such as those from Google and Baidu, provide panoramic street views with geographic location information. Moreover, with the rapid development of machine learning, new tools are being developed to recognize and extract SVI elements, such as greenery, buildings, pedestrians, and tree shade, for further processing (Ye, Zeng, Shen, Zhang, & Lu, 2019). Machine learning has also been used to detect pedestrians in SVI with satisfactory accuracy and efficiency (Chen et al., 2020; Yin et al., 2015). Furthermore, SVI data have the advantage of only capturing pedestrians on streets, while other big data (e.g., social media data or app user location heatmap data) may be bias to include human activities inside buildings, e.g., dinning in a restaurant, or watching a movie.

1.4. Research gaps and our study

To date, researchers have advocated the concept of walkability and conducted in-depth research on the relationship between built environments and various walking behaviors. However, few studies have distinguished between the two dimensions of walking behaviors, i.e., individual and collective. Although individual and collective walking behaviors are closely related, spatial disparities may exist between them. Moreover, a person's total walking time may not be affected by an intervention that has been applied to improve collective walking behavior in one area. For example, people may choose to walk more in areas close to their offices and to walk less in other areas, such as around their residence. Therefore, although their total walking time will not change, the pedestrian volume in an area may increase. Moreover, some people's individual walking behaviors may have a negative relationship with collective walking behaviors. For example, some people may prefer to walk less in areas with high pedestrian volume due to overcrowding or noise. If such spatial disparity exists between these two types of walking behaviors, it is critical to distinguish them and also identify which urban design features are linked to which behaviors.

To address the abovementioned research gaps, in this study we distinguished between individual walking behaviors and collective walking behaviors. Individual walking behavior was determined by measuring the walking durations of 59,000 participants via a population-level survey. Collective walking behavior was determined by measuring the pedestrian volume for all streets in a city, extracted from 219,248 SVIs using machine learning. Moreover, built environment characteristics in the 5D framework and eye-level built environment characteristics were assessed. The objectives of this research were: (i) to explore whether any spatial disparity existed between the two types of walking behaviors; and (ii) to investigate whether built environment characteristics had different relationships with these two types of behaviors.

This study contributes to academic research and society in three aspects: First, it is one of the first studies to distinguish between individual and collective walking behaviors, as thus clarified the complexity of walking behaviors. Second, it used a novel method, based on SVIs and machine learning, to capture pedestrian volume; this method can accurately and effectively assess citywide collective walking behaviors. Third, it examined how built environment characteristics affect these two types of walking behaviors. The findings of this study will assist government officials and urban planners to develop effective intervention strategies to stimulate one or both types of walking behaviors.

2. Methods

2.1. Research area and spatial unit

Hong Kong is a high-density global city situated in the southeastern region of China. It has a total land area of 1,102 km^2 (Census & Statistics Department of Hong Kong, 2020) and consists of three major areas: Hong Kong Island, Kowloon, and the New Territories (Fig. 1). In 2020, Hong Kong had a total population of 7.47 million, with a gross population density of 6,890 persons per km^2 (Census & Statistics Department of Hong Kong, 2020). Its population density is even higher in the built-up (developed) areas, which account for only approximately 25% of the whole territory, while the remaining land is preserved for country parks or natural areas.

First, we generated a fishnet of 500×500 m rectangular grids covering all built-up areas in Hong Kong, to serve as units of analysis. The grids in which only one type of walking data was available were discarded, which left a total of 1,049 grids for which individual walking data and collective walking data were available.

2.2. Outcome variables: Individual walking behaviors and collective walking behaviors

Individual walking behavior data were acquired from the Household Interview Survey (HIS), one of the three main surveys of the Hong Kong Travel Characteristics Survey of 2011 (HKTCS 2011), which aimed to analyze the travel behaviors of Hong Kong residents. The household interview surveys were conducted between 2011 and 2012 by trained interviewers, to collect participants' one-day travel records. Participants were asked to recall all of their trips taken on the day before the survey. In addition, participants were asked to provide detailed walking-trip information, including trip start-time and end-time, and trip origin and destination. All participants' residence locations were geocoded and assigned in corresponding fishnet grids using ArcGIS 10.5. Finally, the average daily walking time per person for all residents within a grid was used to represent individual walking behaviors in that grid.

Collective walking behavior was assessed by pedestrian volume on streets. To obtain pedestrian volume data, SVIs in Hong Kong

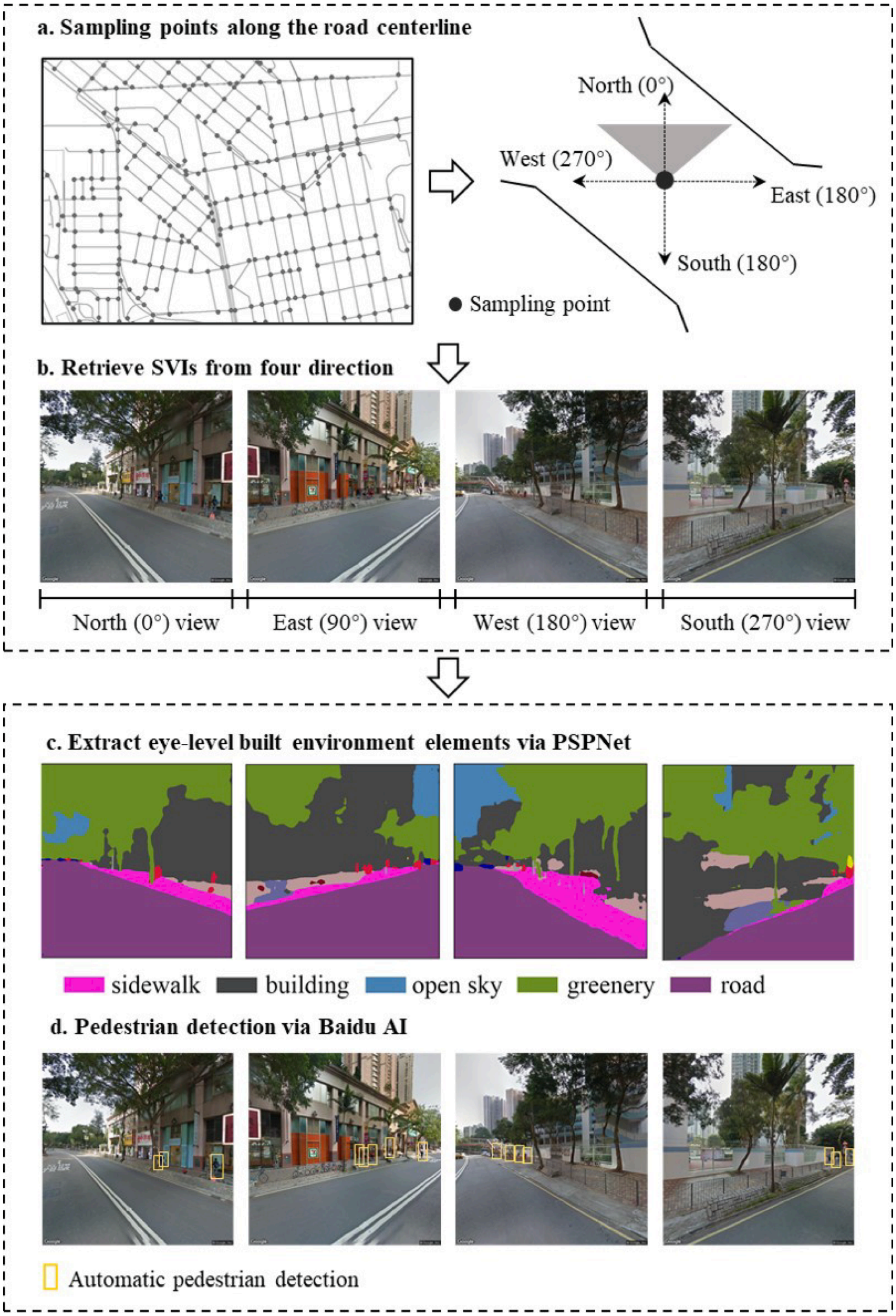

Fig. 2. Assessing collective walking behaviors (e.g., pedestrian volume) and streetscape features from Google Street View images: a) Sampling points were distributed every 50 m along the road centerline. b) In each sampling point, four images were retrieved in the North (0°), East (90°), South (180°), and West (270°) directions. c) Image segmentation using machine learning technique. d) Pedestrian detection using the pedestrian-counting feature of AI.

were retrieved using the Google application programming interface (API) (https://developers.google.com/maps). SVIs have been validated as an efficient and reliable data source for the estimation of street-level pedestrian volumes (Chen et al., 2020; Yin et al., 2015). According to a study of large-scale validation, pedestrian volume estimation using SVIs can provide acceptable (Cronbach's alpha ≥ 0.70) or good (Cronbach's alpha ≥ 0.80) levels of accuracy compared with field observation (Chen et al., 2020). The default search radius of the Google Street View API is 50 m. Thus, to improve the spatial representation, SVIs were collected every 50 m along all street segments in the study area. Hence, SVIs were collected from 54,812 sampling points along 31,971 street segments in Hong Kong, to give a total length of 4,564 km. We also developed a Python script to collect SVIs via the API. Accordingly, based on the coordinates of each sampling point, four SVIs with a 90° field of view were retrieved from Google Street View panorama. The heading parameters of the four retrieved images were set at 0°, 90°, 180°, and 270°, for North, East, South, and West directions, respectively. We also set other image-retrieving parameters, namely a pitch of 0° and size of 640 × 480 pixels. Thereafter, the pedestrian counting feature of Baidu AI (https://ai.baidu.com/tech/body/num) was used through the corresponding API to count the pedestrians in the images (Fig. 2). In a pilot study of 50 randomly selected images, Baidu AI was highly accurate relative to expert judgment (Pearson's r = 0.94). Hence, the number of pedestrians in one sampling point was regarded as the number of pedestrians detected in the four street view images. Finally, the pedestrian volume in each fishnet grid was estimated as the average number of pedestrians in all of the sampling points within that grid.

2.3. Macro-scale built environment characteristics

Two types of built environment characteristics were assessed: macro-scale and micro-scale characteristics. Macro-scale built environment characteristics were measured using the 5D framework comprising density, destination accessibility, distance to transit, diversity, and design (Ewing & Cervero, 2010a). In addition, urban green space was considered as an important built environment indicator that might affect walking (Gao, Kamphuis, Helbich, & Ettema, 2020).

Density was measured in terms of the building floor area (m^2) in each grid. Diversity was measured by land-use mix, considering the ratios of different land-use types in each grid. Three land-use categories were considered in this study, including residence, retail and office, which were retrieved from Planning Department of Hong Kong. The entropy score of the land-use mix was calculated as follows (Shannon, 1948):

$$\text{Mixindex} = (-1) \times [(b_1/a)\ln(b_1/a) + \cdots + (b_n/a)\ln(b_n/a)] \tag{1}$$

where $b_i$denotes the area of type i land use, a is the total area of land use, and n is the total number of land-use types present in the spatial unit.

The design was operationalized according to the number of street intersections (three or more streets) and road density in each grid. The road density was represented by the road length in each grid. The destination accessibility was measured based on the number of points of interest (POIs) in each grid, and the numbers of commercial, public service, catering, education, and tourist spot POIs in each grid were calculated (http://map.baidu.com). The distance to transit was evaluated as the number of bus stops, and the distance to the nearest mass transit rail (MTR) station in each grid.

Finally, the number of urban green spaces was determined in terms of urban park areas and the normalized difference vegetation index (NDVI) in each grid. The NDVI was calculated by a cloud-free Sentinel-2 remote-sensing image taken in July 2018 (Drusch et al., 2012), using the following equation: NDVI = (NIR − Red)/(NIR + Red), where Red and NIR refer to the spectral reflectance measurements obtained by the red light and near-infrared regions, respectively. NDVI values range between − 1.0 and 1.0, the higher the NDVI value, the higher level of green vegetation. The average NDVI value within a grid was used to measure the overall urban greenness in the grid.

2.4. Micro-scale built environment characteristics

Micro-scale built environment characteristics refer to streetscape features that pedestrians can perceive at eye level, and were extracted from SVIs segmented by machine learning technique, PSPNet (Zhao, Shi, Qi, Wang, & Jia, 2017), which is an effective machine-learning algorithm for scene parsing and semantic segmentation via a pyramid-pooling module and a pyramid scene-parsing network. This approach has been used to achieve state-of-the-art pixel-level prediction performance on various datasets, such as Cityscapes (Zhao et al., 2017). A pre-trained Cityscapes model was used to segment each SVI into 19 categories of ground objects. We calculated the pixel ratio of each object on the ground in an image. The four images retrieved for each sampling point were used for image segmentation with PSPNet (Fig. 2), to measure the mean quantity of streetscape features in each sampling point. We chose greenery, open sky, building, and road as features to represent the micro-scale built environment, because these features have been associated with walking behaviors (Yin, 2017). Finally, the average proportion of each streetscape feature at the sampling points in each grid was calculated to represent the micro-scale features for that grid.

2.5. Spatial regression analysis

First, we tested the multicollinearity between the independent variables using the variance inflation factor (VIF). All variables with a VIF of > 4 were excluded from the follow-up analysis. Hence, the catering POIs and the ratio of buildings in SVIs were excluded.

Second, two ordinary least square (OLS) regression models were created to predict pedestrian volume and individual walking time with the built environment factors respectively. Due to the outcomes of nearby grids may be spatially correlated, i.e., grids which are close to each other, may have similar walking outcomes than grids which are far away from each other (Fischer & Getis, 2010). Hence, the spatial autocorrelation of OLS model's residual was assessed to determine whether spatial regression models should be used. The OLS model equation is expressed 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.

We assessed the spatial autocorrelation of two OLS models' residuals with Moran's I test (Wang, Shi, Fang, & Feng, 2019). Moran's I is defined as follows:

$$I = \frac{n\sum_i \sum_j \omega_{ij} \times (x_i - \overline{x})(x_j - \overline{x})}{\left(\sum_i \sum_j \omega_{ij}\right) \times \sum_i (x_i - \overline{x})^2} \tag{3}$$

Where the n is the number of 500 × 500 m grids; x_i and x_j represents the residual of i and j, respectively; ω_{ij} is the spatial weight matrix. In this study, we applied queen contiguity as the definition rule of spatial weight calculation, using GeoDa software (version 1.18).

As shown by the results, there was significant spatial autocorrelation for both pedestrian volume (Moran's I = 0.143; $p < 0.001$) and individual walking time (Moran's I = 0.113, $p < 0.001$). Hence, spatial regression models should be taken into consideration in this study. Two major spatial regression models, spatial lag model (SLM) and spatial error model (SEM) (Anselin, 2013; Anselin & Rey, 1991), introduce spatial autocorrelation in regression model by spatial lag dependence and spatial error dependence respectively (Fischer & Wang, 2011). The SLM assumes that the spatial autocorrelation is included as dependent variable, yet the SEM considers spatial autocorrelation as the error term.

In order to select the spatial regression model which can best fit the data of the two walking behaviors, in step three we conducted Lagrange multiplier (LM) pre-tests (Anselin, Syabri, & Kho, 2010). Four LM test statistics were applied as the diagnostic criteria, i.e., LM (lag), Robust LM (lag), LM (error) and Robust LM (error). Table 1 presented the outcomes of LM test of the two walking behaviors. For pedestrian volume, while Robust LM(lag) was significant ($p < 0.001$), Robust LM (error) was not ($p = 0.572$), indicating the presence of a missing spatial lag variable. The same patten applies to individual walking time, i.e., Robust LM(lag) was significant ($p < 0.001$), Robust LM (error) was not ($p = 0.064$).

Hence, we selected SLM rather than SEM in this study to minimize the spatial effects of the two types of walking data. Both the OLS and SLM were conducted using Geoda. The SLM can be written as follows:

$$y = \rho \mathrm{W_y} + \mathrm{X}\beta + \varepsilon \tag{4}$$

where ρ is the spatial lag parameter, and $\mathrm{W_y}$ is a vector of spatial weights (a row of the spatial weights matrix).

3. Result

3.1. Descriptive statistics

The descriptive statistics of the pedestrian volume, individual walking time, and built environment characteristics in a grid are presented in Table 2. The average pedestrian volume in each grid was 95.020 (SD = 265.067); that is, there were an average of approximately 95 pedestrians in a 500 × 500 m area. This relatively high pedestrian volume indicated high levels of pedestrian activities and urban vitality in Hong Kong. There were notable spatial variations in the pedestrian volume between different areas, ranging from 0 to 3,339 pedestrians. The average and median individual daily walking time were 10.318 min and 9.754 min respectively, which is in line with the previous findings (Lu, Yang, Sun, & Gou, 2019).

The ratios of road (M = 0.276, SD = 0.059) and greenery (M = 0.289, SD = 0.166) in the SVIs were higher than that of open sky (M = 0.100, SD = 0.059).

For the macro-scale built environment, the study areas generally had high building density (M = 2835564.906 m^2, SD =

Table 1
Lagrange multiplier (LM) diagnostics for spatial dependence.

Walking behavior variable	Statistic	DF	Value	*p*-value
Pedestrian volume	Lagrange Multiplier (lag)	1	31.125	< 0.001***
	Robust LM (lag)	1	11.321	< 0.001***
	Lagrange Multiplier (error)	1	20.122	< 0.001***
	Robust LM (error)	1	0.318	0.572
Individual walking time	Lagrange Multiplier (lag)	1	45.304	< 0.001***
	Robust LM (lag)	1	41.775	< 0.001***
	Lagrange Multiplier (error)	1	9.522	0.012*
	Robust LM (error)	1	2.993	0.064

Note: DF = Degrees of freedom; LM = Lagrange multiplier; *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 2
Descriptive Statistics for walking behaviors and built environment characteristics of the research area in Hong Kong, which was tessellated into 1049 500 × 500 m rectangular grids.

Variables (unit)	Minimum	Maximum	Mean	Median	SD
Dependent variables					
Pedestrian volume (*N*)	0	3339	95.020	12	265.067
Individual walking time (min.)	2	29.486	10.318	9.754	3.787
Independent variables					
Micro-scale built environment					
Road	0	0.431	0.276	0.291	0.059
Greenery	0	0.964	0.289	0.264	0.166
Open sky	0	0.415	0.100	0.089	0.059
Macro-scale built environment					
Building floor area(m^2)	0	2835564.906	248676.103	119356.100	315254.052
Land-use mix ($\geq$0)	0	1.000	0.504	0.435	0.299
Street intersection (*N*)	0	61	12.236	10	10.230
Road density (m)	0	14709.404	4560.034	4204.259	2525.045
Park POI (N)	0	8	0.699	0	1.203
Commercial POI (*N*)	0	30	2.653	1	4.716
Education POI (*N*)	0	25	2.257	1	3.299
Public service POI (*N*)	0	10	0.982	0	1.696
Tourist spot POI (*N*)	0	49	3.679	2	5.806
Distance to MTR (m)	22.851	10217.695	1753.477	1124.264	1634.800
Transit stops (*N*)	0	34	4.599	2	5.779
NDVI	0	0.668	0.257	0.248	0.178

Note: *N* = Number; SD = Standard deviation; POI = Point of interest; MTR = Mass transit rail; NDVI = Normalized difference vegetation index.

315254.052) and diversified land use (M = 0.504, SD = 0.299). The areas also had a well-connected street network, with numerous street intersections (M = 12.236, SD = 10.230) and a high road density (M = 4560.034 m, SD = 2525.045). In terms of the POIs, there were more tourist spots, commercial centers, and education facilities than parks and public service centers.

3.2. Spatial mismatch between the two walking behaviors

We classified all grids as areas with high or low collective walking, according to the median value of pedestrian volume (Fig. 3a). Similarly, we classified the grids into areas with high or low individual walking, according to the median value of individual walking time (Fig. 3b).

Accordingly, the grids could be divided into four groups (Fig. 4 and Table 3): areas with high collective walking and high individual walking (H/H areas); areas with high collective walking and low individual walking (H/L); areas with low collective walking and high individual walking (L/H); and areas with low collective walking and low individual walking (L/L).

In Fig. 4, it can be seen that the H/H areas were mainly located on the perimeter of the dense urban areas of Hong Kong Island (e.g., Happy Valley) and Kowloon (e.g., Tsim Sha Tsui and Kowloon Tong), and in new established towns in the New Territories (e.g., Shatin and Tsuen Wan). The H/L areas were located in the core areas of the Hong Kong Island (e.g., Central and Causeway Bay), Kowloon (e.g., Yau Ma Tei and Mong Kok), and new towns in the New Territories (e.g., Tuen Mun and Kwai Chung). The L/H areas were mainly located in towns and villages in the New Territories (e.g., Yuen Long and Sai Kung), while a small number of H/L areas were located on the fringes of Hong Kong Island and Kowloon (e.g., Stanley and Mei Foo Sun Chuen). The L/L areas were scattered in the *peri*-urban areas of Hong Kong Island (e.g., Big Wave Bay), Kowloon (e.g., Ma Yau Tong), and the New Territories (e.g., Tai Mong Tse Tsuen), which were characterized by relatively poor street connectivity and inconvenient public transportation.

Urban planners' and government officials' priorities for urban design interventions for these four types of areas are different. The H/H areas attract more pedestrians, and pedestrians also walk longer in such areas. Therefore, urban design interventions may have a high impact, because they will affect many people, who will have prolonged exposure to the interventions. In contrast, the L/L areas attract fewer pedestrians and people walk less in such areas; therefore, interventions in these areas will have a low impact.

The H/L areas attract more pedestrians, but people walk less in these areas. Interventions here will have a medium–high impact, for two reasons. First, the interventions can affect more people, although their exposure to the interventions will be short. Second, the built environment characteristics have stronger relationships with collective walking behaviors than with individual walking behaviors. In contrast, the L/H areas have fewer pedestrians, but people walk more in such areas. Interventions in these areas will have a medium–low impact, because they will affect fewer people, but these people will have long exposure to the interventions. In addition, built environment characteristics have relatively weak relationships with individual walking behaviors.

3.3. Relationships between the built environment and two types of walking behaviors

Table 4 and Fig. 5 present the relationships between the built environment and both pedestrian volume and individual walking time. For both types of walking behaviors, the SLM have a better performance than OLS model in terms of goodness-of-fit (R^2, Log-likelihood, Akaike info criterion and Schwarz criterion), so we mainly concentrate on the SLM results in this paper. Land-use mix,

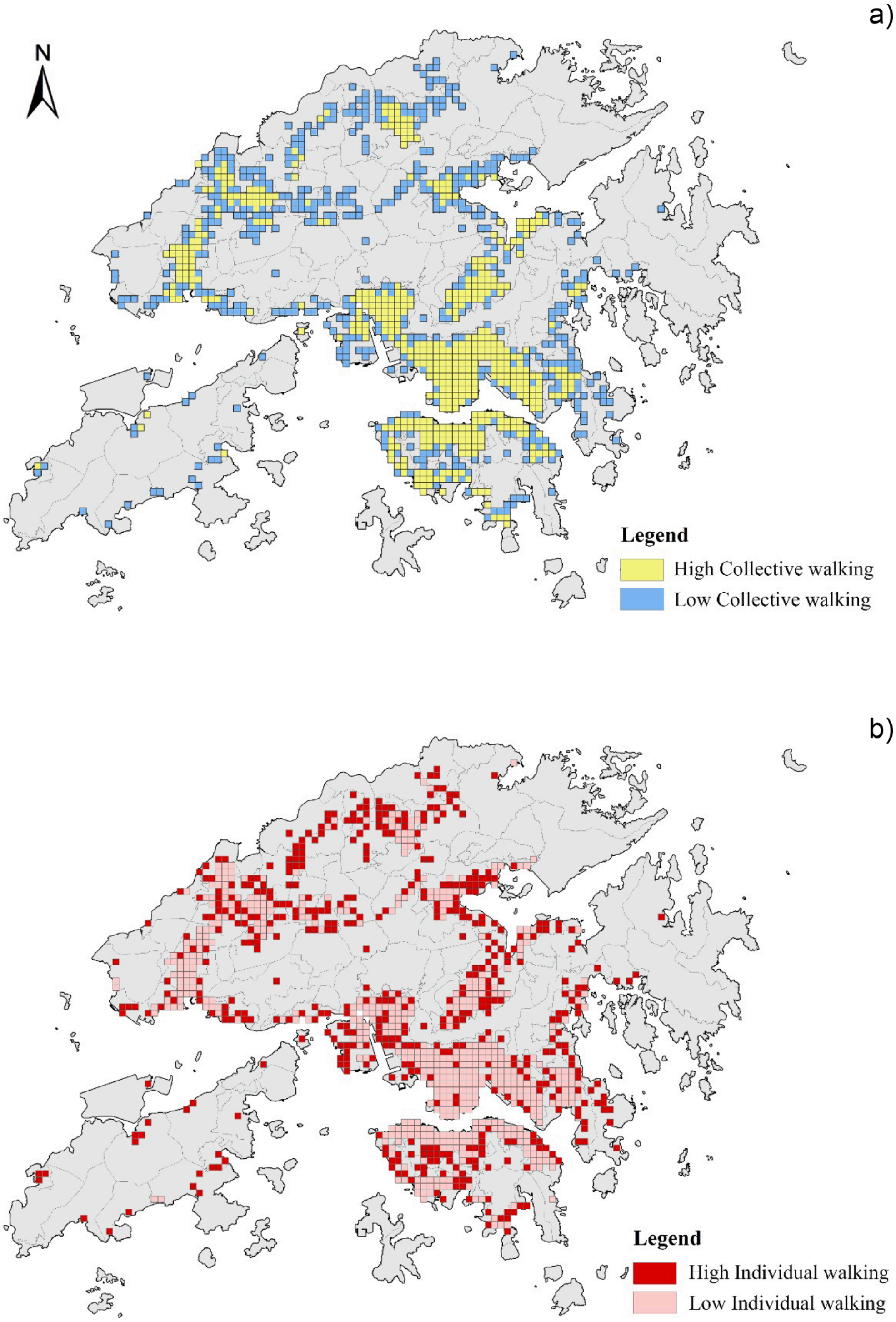

Fig. 3. Areas with a) high/low collective walking behaviors, and b) high/low individual walking behaviors.

the number of transit stops, distance to MTR stations, commercial POIs, tourist spot POIs, and street intersections showed positive relationships with pedestrian volume. The ratio of roads in SVIs, education POIs, and public service POIs showed negative relationships with pedestrian volume. The overall R^2 of model 2 reached 0.675, indicating that our model could explain 67.5% of the variance in pedestrian volume across all grids.

Greenery from SVIs, NDVI, land-use mix, and distance to MTR were positively correlated with individual walking time. However, tourist spot POI was negatively correlated with individual walking time. The overall R^2 of model 4 reached 0.341, indicating that our

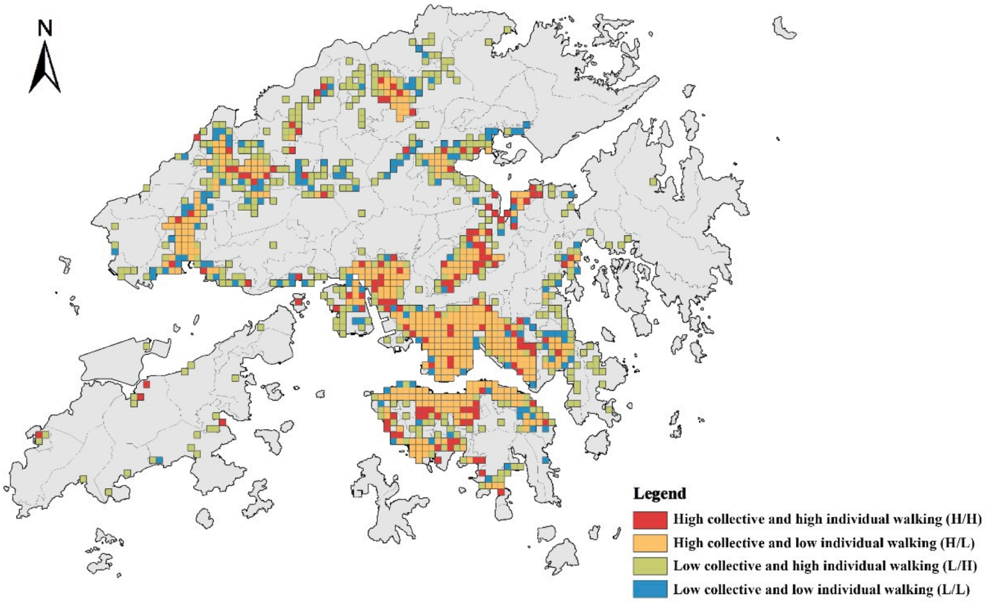

Fig. 4. Classification of urban areas into four groups, according to the collective and individual walking outcomes.

Table 3
Impact levels of fishnets for planning interventions. Source: Google Inc.

Types of areas	Location	Impact of urban design interventions	Representative example
H/H (high collective walking, high individual walking)	Happy Valley, Tsim Sha Tsui, Tsuen Wan	1) High impact	
H/L (high collective walking, low individual walking)	Yau Ma Tei, Central, Tuen Mun	2) Medium–high impact	
L/H (low collective walking, high individual walking)	Stanley, Yuen Long, Mei Fo Sun Chuen	3) Medium–low impact	
L/L (low collective walking, low individual walking)	Ma Yau Tong, Big Wave Bay, Tai Mong Tse Tsuen	4) Low impact	

model could explain 34.1% of the variance in individual walking time across all grids.

4. Discussion

There is renewed interest among researchers and planning practitioners in creating pedestrian-friendly urban environments and improving walkability. However, the term “walkability” has two meanings, and is associated with two related but distinct walking behaviors: individual walking behaviors and collective pedestrian activities. This study is among the first to clarify the spatial disparity between these two types of walking behaviors, and to identify the urban design features linked to each. The three main findings of this research are described below.

Table 4
Results of regression model of built environment, collective walking, and individual walking. (fishnet = 500 × 500 m, N = 1049).

Model predictors	Pedestrian volume				Individual walking time			
	Model 1 (OLS)		Model 2 (SLM)		Model 3 (OLS)		Model 4 (SLM)	
	Coef. (SE)	p-value	Coef. (SE)	p-value	Coef. (SE)	p-value	Coef. (SE)	p-value
Micro-scale built environment								
Road	−329.209 (100.878)	0.001**	−290.895 (98.170)	0.003**	−2.902 (2.067)	0.160	−3.612 (2.084)	0.083
Greenery	−55.345 (47.061)	0.239	−38.252 (45.858)	0.404	2.340 (0.964)	0.015*	2.630 (0.978)	0.007**
Open sky	−11.211 (103.202)	0.913	60.492 (101.177)	0.549	2.551 (2.115)	0.228	2.103 (2.231)	0.345
Macro-scale built environment								
Building floor area	0.000 (0.000)	0.870	0.000 (0.000)	0.983	−0.000 (0.000)	0.713	−0.000 (0.000)	0.801
Land-use mix	55.366 (17.848)	0.001**	50.361 (17.408)	0.003**	1.115 (0.365)	0.002**	0.856 (0.395)	0.030*
Road density	−0.004 (0.003)	0.158	−0.003 (0.002)	0.158	0.000 (0.000)	0.415	0.000 (0.000)	0.566
Transit stops	5.187 (1.528)	< 0.001***	4.849 (1.486)	0.001**	−0.038 (0.031)	0.219	−0.027 (0.031)	0.379
Distance to MTR	0.005 (0.003)	0.132	0.007 (0.003)	0.021*	0.000 (0.000)	< 0.001***	0.000 (0.000)	< 0.001***
NDVI	−10.725 (38.608)	0.781	16.902 (37.756)	0.654	1.885 (0.791)	0.017*	1.730 (0.822)	0.026*
Park POI	1.679 (4.071)	0.680	−3.363 (4.010)	0.401	−0.050 (0.083)	0.548	−0.040 (0.081)	0.620
Commercial POI	36.540 (1.817)	< 0.001***	36.069 (1.768)	< 0.001***	−0.055 (0.037)	0.136	−0.040 (0.036)	0.263
Education POI	−11.948 (2.033)	< 0.001***	−12.223 (1.978)	< 0.001***	−0.084 (0.041)	0.043*	−0.061 (0.041)	0.134
Public Service POI	−19.055 (3.940)	< 0.001***	−16.713 (3.835)	< 0.001***	−0.096 (0.080)	0.233	−0.066 (0.077)	0.395
Tourist spot POI	5.195 (1.355)	< 0.001***	4.793 (1.321)	< 0.001***	−0.070 (0.027)	0.011*	−0.068 (0.026)	0.010*
Street intersection	4.533 (0.898)	< 0.001***	4.116 (0.876)	< 0.001***	−0.031 (0.018)	0.095	−0.036 (0.018)	0.055
R^2	0.661		0.675		0.303		0.341	
LL	−6773.35		−6756.77		−2695.37		−2674.45	
AIC	13578.77		13547.55		5422.73		5380.91	
SC	13658.15		13631.82		5502.02		5460.19	

Note: OLS = Ordinary least squares; SLM = Spatial lag model; Coef. = Coefficient; SE = Standard error; *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$; POI = Point of interest; MTR = Mass transit rail; NDVI = Normalized difference vegetation index; LL = Log likelihood; AIC = Akaike info criterion; SC = Schwarz criterion.

First, it was found that spatial disparity exists between collective and individual walking behaviors. There are notable spatial mismatches between areas with high/low pedestrian volume and those with high/low individual walking time. Areas with high pedestrian activities may not necessarily encourage individuals to walk, and vice versa.

All urban areas can be classified into four groups, according to a combination of the two types of walking behaviors (Table 3, Fig. 4, Appendix A). The areas in these four groups have unique built environment characteristics, which are as follows. (1) H/H areas: urban areas with high collective and individual walking behaviors, which are characterized by mixed land use, convenient public transportation systems, well-connected street networks, and high accessibility to pedestrian destinations. These features are conducive to high pedestrian volume. Furthermore, these areas have sufficient urban green spaces, which are vital to encourage individual walking behaviors, especially walking for leisure, because these spaces provide a pleasant and comfortable walking environment in densely developed urban areas. (2) H/L areas: areas with built environment features that are similar to those of H/H areas, but which have a high concentration of commercial destinations and less greenery exposure. As a result, such built environments attract a large flow of pedestrians for mainly utilitarian purposes, such as going to a restaurant or a shop. Individuals do not walk long for recreational purposes in these areas. (3) L/H areas: these primarily comprise residential areas, far away from commercial districts; they are primarily used by local residents, and hence have low pedestrian flows. However, individuals walk longer in these areas, for utilitarian and recreational purposes, because of the availability of adequate daily pedestrian destinations and a high number of green spaces. (4) L/L areas: these have poor street connectivity, inconvenient public transportation, and insufficient pedestrian destinations, and are often dominated by remote villages or industrial land use, such as warehouses and junkyards. Therefore, automobiles replace walking and public transit as the major transportation mode in these areas.

From a theoretical perspective, this spatial disparity further clarifies walking behaviors, as it shows that pedestrian volume on a street may not accurately reflect people's daily walking or active travel behaviors. In a high-density Asian metropolis, several areas may have high pedestrian flows and urban vitality, owing to high urban densities, mixed land use, and well-connected street networks. However, although such conditions are necessary, they are not solely able to improve individual walking behaviors, as pleasant and comfortable urban environments, such as accessible green spaces, may also be needed. Likewise, residential areas where residents walk longer may not necessarily have high pedestrian volume or urban vitality, as mixed land use and adequate commercial destinations

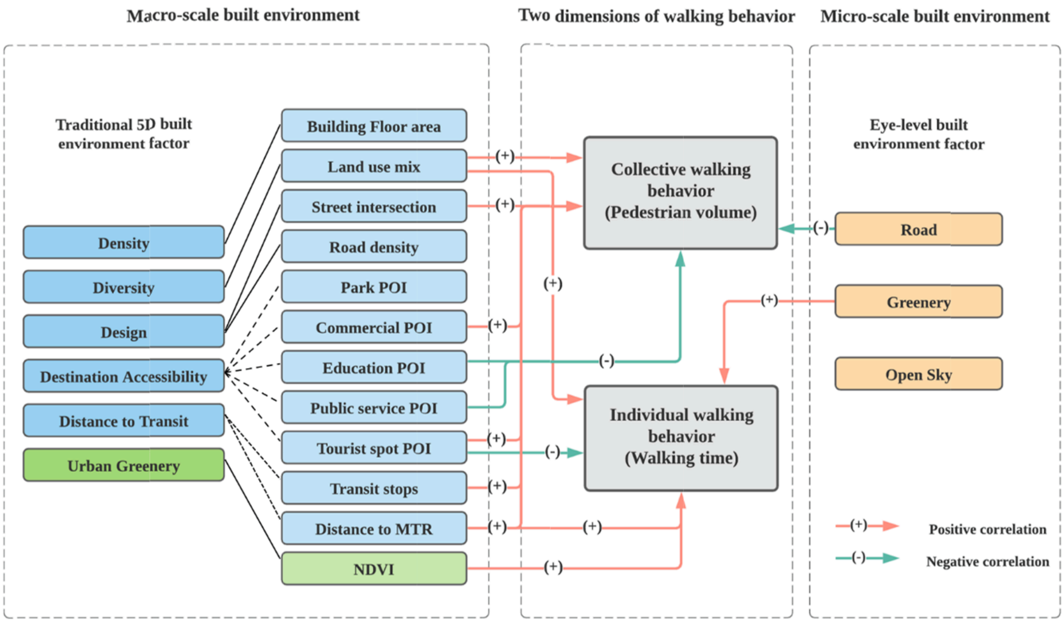

Fig. 5. Relationships between built environment elements and two walking behaviors (result of SLM).

may be required. Hence, we propose that it is critical to distinguish between these two types of walking behaviors, to disentangle the complex relationship between walking behaviors, public health, and urban vitality.

This finding also has important design implications. For example, an H/H area attracts heavy pedestrian flow, and individuals in such areas are willing to walk. Therefore, urban design and planning interventions in such areas will have the largest impact on both types of walking behaviors, thereby improving the effectiveness of government expenditure.

Second, built environment characteristics have stronger relationships with collective walking behaviors than with individual walking behaviors. The combination of all of our built environment characteristics can approximately account for two-thirds of the variance in pedestrian volume, whereas it can only account for one-third of the variance in individual walking time. This is in line with the findings of previous research on pedestrian volume (Lai & Kontokosta, 2018) or individual walking behaviors (Zang et al., 2019). The better prediction of collective pedestrian behaviors than individual behaviors can be explained by the following two reasons. (1) According to the socioecological model, personal health behaviors, such as walking, are influenced by an array of factors consisting of individual, social environment, and physical environment levels. Thus, as our built environment–focused model ignores other important factors, such as individual and social environment factors (Adkins, Makarewicz, Scanze, Ingram, & Luhr, 2017), it has weaker predictive power. Moreover, the pedestrian volume measures the degree to which a viable and livable urban area attracts collective pedestrian movement. Individual factors may have less of a role in predicting pedestrian volume, because the average value of individual factors for a large group of people tends to be stable (e.g., the proportion of sex in 100 people sampled from a population). Therefore, the built environment may better predict where people walk instead of personal walking choices (Le, Buehler, & Hankey, 2018). (2) The better prediction of collective pedestrian behaviors may also be explained by the spatial exposure of the built environment. An individual may walk around his/her home, workplace, or even other destinations far away from his/her home or workplace, for different purposes. Hence, it is less accurate to use a 500 × 500 m grid to estimate the area of an individual's daily activity space (Hurvitz & Moudon, 2012). Moreover, the pedestrian volume in a grid is more easily to be influenced by the built environment characteristics of the grid, rather than by those of other areas. For these two reasons, built environment characteristics have a stronger relationship with pedestrian volume than with individual walking behaviors.

The second finding also has important design and planning implications. Urban design or planning interventions may have a stronger ability to increase urban vitality in an area than to promote individual walking behaviors. Hence, built environment interventions may be more effective for redistributing pedestrian movement, i.e., by increasing pedestrian flow in an area receiving an intervention and decreasing pedestrian flow in other areas. These interventions alone may be less effective in promoting individual walking behaviors and helping people to gain health benefits; in this context, additional interventions at a personal or social level (e.g., education or programs to promote walking) are indispensable.

Third, the two types of walking behaviors are associated with specific sets of built environment variables (Fig. 5). For example, diversity, measured by land-use mix, is positively linked to pedestrian volume and individual walking time, which is consistent with previous findings (Lee et al., 2020; Lu, Xiao, & Ye, 2017). A high level of land-use mix can help to lessen travel distance, encourage walking behavior (Ewing & Cervero, 2010a), and blur the boundary between utilitarian and leisure walking behaviors (Dean et al., 2020). Our study also confirms that street connectivity is significantly related to pedestrian flow (Christiansen et al., 2016; Hajrasouliha & Yin, 2015). A well-connected street network increases the potential pedestrian destinations in one area and helps pedestrians to reach more destinations within walking distance; hence, it increases neighborhood vitality (Lerman, Rofè, & Omer, 2014).

Furthermore, the accessibilities of different types of destinations have different relationships with different types of walking behaviors. Commercial POI is positively correlated with pedestrian volume; that is, areas with more commercial establishments are likely to attract more people (Hahm, Yoon, Jung, & Kwon, 2017). Tourist spot POI is positively correlated with pedestrian volume, but negatively correlated with individual walking time. Tourist spot POIs may attract a large number of tourists (Lee et al., 2020); however, they may cause problems to local residents, such as traffic congestion and overloading of service supporting facilities, which will deter residents' willingness to walk. Moreover, education and public service POIs are negatively correlated with pedestrian volume, as schools and public service facilities are generally situated in quiet areas and only used by specific people.

The ratio of road in SVIs shows a negative relationship with pedestrian volume. Wide roads with a large traffic volume are often accompanied by exhaust and noise pollution, which negatively affect pedestrian gathering (Kim et al., 2016). In contrast, narrower streets are conducive to collective pedestrian movement, as they improve shading and the sense of street enclosure (Ewing & Clemente, 2013). For subtropical cities like Hong Kong, it is important to create a shaded walking environment to improve pedestrians' thermal comfort (Manavvi & Rajasekar, 2021).

In addition, overall urban greenery levels (measured by NDVI from satellite images) and eye-level greenery (measured by the ratio of greenery in SVIs) are positively and independently associated with individual walking time. These results are in accordance with previous research (Lu et al., 2019). The presence of greenery may stimulate individual walking behaviors by providing shaded and pleasant environments (Christiansen et al., 2016; Kim et al., 2016). Therefore, to stimulate individual walking behaviors, urban planners and policymakers should simultaneously consider traditional greenness indicators, such as vegetation coverage, and residents' eye-level greenery exposure (Xie et al., 2021).

Furthermore, no obvious evidence of a relationship between building density and the two types of walking behaviors have been found. In European and North American cities, density often shows a positive relationship with walking behaviors (Christiansen et al., 2016; Hajrasouliha & Yin, 2015); however, in Latin American and Asian cities, there is no apparent connection between these factors (Hermida et al., 2019; Kim et al., 2016; Lee et al., 2020), probably because Latin American and Asian cities have a higher density built environment than European and American cities. Moreover, there may be a threshold effect between density and walking behavior (Christiansen et al., 2016; Lu et al., 2017). That is, in low- and medium-density urban environments (e.g., European and North American cities), increasing density may increase walking; however, in high-density urban environments (e.g., Latin American and Asian cities), increasing density may not increase walking, and may even decrease walking (Lu et al., 2017).

5. Limitation

The limitations of this study are as follows: First, the study did not separately investigate walking behaviors on weekends and those on weekdays, or in other time frames, because of data limitations. However, as these walking behaviors may feature temporal fluctuations, such as varied spatial patterns on different days or even in different periods of a day (Gao et al., 2020), further studies are needed to explore such temporal fluctuations, to comprehensively depict walking behaviors. Second, the HKTCS 2011 data were stratified by district, housing type, gender, and age group. Hence, the sample size in densely populated areas (e.g., downtown or residential areas) is larger than that in low-density areas (e.g., villages, country parks). The uneven sample size of the number of interviewed residents and number of individual walking time in a grid (mean = 106.72, SD = 192.36) may lead to the poor fit of the regression models to predict individual walking time. Third, as a typical high-density Asian city, Hong Kong has a three-dimensional pedestrian network consisting of sidewalks, pedestrian bridges, underground passages, and indoor spaces (Cerin et al., 2020). Hence, pedestrian volumes may have been underestimated in the investigated locations, because our SVIs generally omitted pedestrians in locations other than sidewalks. Other novel methods are needed, such as those based on app user data or cellular data, to collect pedestrian movements in footbridges, underground passages, and indoor spaces. Fourth, the study focused on objectively measured built environment features. To enrich the built environment framework, future research may also consider perceptual and subjective characters of the built environment, such as aesthetics and safety (Zhang et al., 2018).

6. Conclusion

To clarify the relationship between the built environment and walking, and to promote the creation of walkable urban environments, we distinguished two types of walking behaviors: collective pedestrian movement (i.e., collective walking) and individual walking time (i.e., individual walking). This distinction revealed that there was a noticeable spatial mismatch between these two types of walking behaviors. All urban areas can be classified into four groups, according to their levels of aggregate and individual walking behaviors, and these groups have unique built-environment characteristics. In addition, we found that built environment characteristics have stronger relationships with collective walking behaviors than with individual walking behaviors.

These findings have theoretical and practical implications. They reveal that it is necessary to distinguish these two types of walking behaviors in future studies on the built environment–walking relationship, as this will assist researchers and urban designers to better comprehend and interpret the complicated relationship between the built environment, walking behaviors, public health, and urban vitality.

Funding

The work described in this paper was fully supported by the grants from National Natural Science Foundation of China (Project No.

51778552) and the Research Grants Council of the Hong Kong SAR (Project No. CityU11207520).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Statistics for built environment characteristics of four groups spatial distribution, sampled in 2018 (fishnet = 500 m × 500 m)

Variables (Unit)	Mean (SE)			
	H/H	H/L	L/H	L/L
Dependent variables				
Pedestrian volume (*N*)	46.267 (3.948)	237.667 (20.299)	2.929 (0.160)	3.907 (0.296)
Individual walking time (min)	12.330 (0.182)	7.282 (0.071)	13.760 (0.149)	7.232 (0.147)
Independent variables				
Micro-scale built environment				
Road	0.289 (0.004)	0.292 (0.002)	0.255 (0.004)	0.275 (0.005)
Greenery	0.290 (0.011)	0.196 (0.006)	0.373 (0.009)	0.315 (0.013)
Open sky	0.096 (0.004)	0.084 (0.002)	0.109 (0.004)	0.125 (0.005)
Macro-scale built environment				
Building floor area (m^2)	277,271.570 (24,773.490)	470,185.001 (18,357.115)	70,339.080 (5,936.722)	94,071.651 (9,999.163)
Land-use mix (≥0)	0.554 (0.026)	0.571 (0.016)	0.462 (0.014)	0.383 (0.022)
Street intersection (*N*)	13.438 (0.526)	19.555 (0.584)	6.435 (0.279)	6.614 (0.473)
Road density (m)	5,386.942 (185.472)	5,284.763 (122.137)	3,382.241 (110.221)	3,417.166 (172.208)
Park POI (*N*)	0.685 (0.084)	1.471 (0.076)	0.098 (0.020)	0.229 (0.055)
Commercial POI (*N*)	2.096 (0.246)	6.198 (0.305)	0.156 (0.031)	0.271 (0.078)
Education POI (*N*)	2.712 (0.301)	4.529 (0.185)	0.306 (0.046)	0.836 (0.138)
Public Service POI (*N*)	1.075 (0.127)	2.026 (0.107)	0.129 (0.024)	0.321 (0.082)
Tourist spot POI (*N*)	3.199 (0.372)	7.383 (0.377)	0.905 (0.112)	1.529 (0.201)
Distance to MTR (m)	1,536.658 (124.435)	891.481 (52.733)	2,573.635 (91.164)	2,123.638 (123.857)
Transit stops (*N*)	4.849 (0.366)	9.094 (0.340)	1.071 (0.077)	1.557 (0.158)
NDVI	0.255 (0.011)	0.164 (0.007)	0.341 (0.009)	0.287 (0.017)

Note: SE = Standard error; *N* = Number; H/H = High global walkability high individual walkability area; H/L = High global walkability low individual walkability area; L/H = Low global walkability high individual walkability area; L/L = Low global walkability low individual walkability area.

References

Adkins, A., Makarewicz, C., Scanze, M., Ingram, M., Luhr, G., 2017. Contextualizing Walkability: Do Relationships Between Built Environments and Walking Vary by Socioeconomic Context? J. Am. Plann. Assoc. 83 (3), 296–314. https://doi.org/10.1080/01944363.2017.1322527.

Anselin, L., 2013. Spatial econometrics: methods and models, (Vol. 4):. Springer Science & Business Media.

Anselin, L., Rey, S., 1991. Properties of tests for spatial dependence in linear regression models. Geographical Analysis 23 (2), 112–131.

Anselin, L., Syabri, I., Kho, Y., 2010. GeoDa: an introduction to spatial data analysis. In: Handbook of applied spatial analysis. Springer, pp. 73–89.

Ashihara, Y. (1983). *The aesthetic townscape*.

Ashton, J., Grey, P., Barnard, K., 1986. Healthy cities — WHO's New Public Health initiative. Health Promot. Int. 1 (3), 319–324. https://doi.org/10.1093/heapro/1.3.319.

Barnett, D.W., Barnett, A., Nathan, A., Van Cauwenberg, J., Cerin, E., 2017. Built environmental correlates of older adults' total physical activity and walking: a systematic review and meta-analysis. Int. J. Behav. Nutr. Phys. Activity 14 (1). https://doi.org/10.1186/s12966-017-0558-z.

Booth, F.W., Roberts, C.K., Laye, M.J., 2011. Lack of exercise is a major cause of chronic diseases. Comprehensive Physiology 2 (2), 1143–1211.

Burton, E., 2000. The Compact City: Just or Just Compact? A Preliminary Analysis. Urban Stud. 37 (11), 1969–2006. https://doi.org/10.1080/00420980050162184.

Calthorpe, P., 1993. The next American metropolis : ecology, community, and the American dream. Princeton Architectural Press, New York.

Cambra, P., Moura, F., 2020. How does walkability change relate to walking behavior change? Effects of a street improvement in pedestrian volumes and walking experience. J. Transp. Health 16, 100797. https://doi.org/10.1016/j.jth.2019.100797.

Census & Statistics Department of Hong Kong, 2020. Population Estimates. Retrieved from:http://www.censtatd.gov.hk/hkstat/sub/so150.jsp.

Cerin, E., Barnett, A., Zhang, C.J.P., Lai, P.C., Sit, C.H.P., Lee, R.S.Y., 2020. How urban densification shapes walking behaviours in older community dwellers: a cross-sectional analysis of potential pathways of influence. Int. J. Health Geogr. 19 (1), 14. https://doi.org/10.1186/s12942-020-00210-8.

Chaix, B., Kestens, Y., Duncan, D.T., Brondeel, R., Méline, J., El Aarbaoui, T., Pannier, B., Merlo, J., 2016. A GPS-based methodology to analyze environment-health associations at the trip level: case-crossover analyses of built environments and walking. Am. J. Epidemiol. 184 (8), 579–589.

Chen, L., Lu, Y.i., Sheng, Q., Ye, Y.u., Wang, R., Liu, Y.e., 2020. Estimating pedestrian volume using Street View images: A large-scale validation test. Comput. Environ. Urban Syst. 81, 101481. https://doi.org/10.1016/j.compenvurbsys.2020.101481.

Christiansen, L.B., Cerin, E., Badland, H., Kerr, J., Davey, R., Troelsen, J., van Dyck, D., Mitáš, J., Schofield, G., Sugiyama, T., Salvo, D., Sarmiento, O.L., Reis, R., Adams, M., Frank, L., Sallis, J.F., 2016. International comparisons of the associations between objective measures of the built environment and transport-related walking and cycling: IPEN Adult Study. J. Transp. Health 3 (4), 467–478. https://doi.org/10.1016/j.jth.2016.02.010.

Corburn, J., 2009. Toward the healthy city : people, places, and the politics of urban planning. MIT Press, Cambridge, MA.

Couch, C., Petschel-Held, G., Leontidou, L., 2008. Urban sprawl in Europe: landscape, land-use change and policy. John Wiley & Sons.

Dean, J., Biglieri, S., Drescher, M., Garnett, A., Glover, T., Casello, J., 2020. Thinking relationally about built environments and walkability: A study of adult walking behavior in Waterloo Ontario. Health Place 64, 102352. https://doi.org/10.1016/j.healthplace:2020.102352.

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., Martimort, P., Meygret, A., Spoto, F., Sy, O., Marchese, F., Bargellini, P., 2012. Sentinel-2: ESA's optical high-resolution mission for GMES operational services. Remote Sens. Environ. 120, 25–36.

Ewing, R., Cervero, R., 2010a. Travel and the Built Environment. J. Am. Plann. Assoc. 76 (3), 265–294. https://doi.org/10.1080/01944361003766766.

Ewing, R., Cervero, R., 2010b. Travel and the built environment: a meta-analysis. J. Am. Plann. Assoc. 76 (3), 265–294.

Ewing, R., Clemente, O., Neckerman, K.M., Purciel-Hill, M., Quinn, J.W., Rundle, A. (Eds.), 2013. Measuring Urban Design. Island Press/Center for Resource Economics, Washington, DC.

Fischer, M.M., Getis, A. (Eds.), 2010. Handbook of Applied Spatial Analysis. Springer Berlin Heidelberg, Berlin, Heidelberg.

Fischer, M.M., Wang, J., 2011. Spatial data analysis: models, methods and techniques. Springer Science & Business Media.

Forsyth, A., 2015. What is a walkable place? The walkability debate in urban design. Urban Des. Int. 20 (4), 274–292. https://doi.org/10.1057/udi.2015.22.

Frumkin, H., 2004. Urban sprawl and public health : designing, planning, and building for healthy communities. Island Press, Washington, DC.

Gao, J., Kamphuis, C.B.M., Helbich, M., Ettema, D., 2020. What is 'neighborhood walkability'? How the built environment differently correlates with walking for different purposes and with walking on weekdays and weekends. J. Transp. Geogr. 88, 102860. https://doi.org/10.1016/j.jtrangeo.2020.102860.

Gehl, J., 1987. Life between buildings. Van Nostrand Reinhold, New York.

Gehl, J., 2013. Cities for people. Island press.

Geller, A.L., 2003. Smart Growth: A Prescription for Livable Cities. Am. J. Public Health 93 (9), 1410–1415. https://doi.org/10.2105/ajph.93.9.1410.

Hahm, Y., Yoon, H., Jung, D., Kwon, H., 2017. Do built environments affect pedestrians' choices of walking routes in retail districts? A study with GPS experiments in Hongdae retail district in Seoul, South Korea. Habitat Int. 70, 50–60. https://doi.org/10.1016/j.habitatint.2017.10.002.

Hajrasouliha, A., Yin, L., 2015. The impact of street network connectivity on pedestrian volume. Urban Stud. 52 (13), 2483–2497. https://doi.org/10.1177/0042098014544763.

Hermida, C., Cordero, M., Orellana, D., 2019. Analysis of the influence of urban built environment on pedestrian flow in an intermediate-sized city in the Andes of Ecuador. Int. J. Sustain. Transport. 13 (10), 777–787. https://doi.org/10.1080/15568318.2018.1514445.

Howard, E., 1965. Garden cities of tomorrow. Faber, London.

Hurvitz, P.M., Moudon, A.V., 2012. Home Versus Nonhome Neighborhood: Quantifying Differences in Exposure to the Built Environment. Am. J. Prev. Med. 42 (4), 411–417. https://doi.org/10.1016/j.amepre.2011.11.015.

Jacobs, J., 1965. The death and life of Great American cities. Penguin in association with Jonathan Cape, Harmondsworth.

Kang, B., Moudon, A.V., Hurvitz, P.M., Reichley, L., Saelens, B.E., 2013. Walking objectively measured: classifying accelerometer data with GPS and travel diaries. Retrieved from Med. Sci. Sports Exerc. 45 (7), 1419. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3674121/pdf/nihms-442394.pdf.

Kelly, P., Williamson, C., Niven, A.G., Hunter, R., Mutrie, N., Richards, J., 2018. Walking on sunshine: scoping review of the evidence for walking and mental health. Br. J. Sports Med. 52 (12), 800–806. https://doi.org/10.1136/bjsports-2017-09882710.1136/bjsports-2017-098827.supp110.1136/bjsports-2017-098827.supp2.

Kenworthy, J.R., 2006. The eco-city: ten key transport and planning dimensions for sustainable city development. Environ. Urbanization 18 (1), 67–85.

Kim, T., Sohn, D.-W., Choo, S., 2016. An analysis of the relationship between pedestrian traffic volumes and built environment around metro stations in Seoul. KSCE J. Civ. Eng. 21 (4), 1443–1452. https://doi.org/10.1007/s12205-016-0915-5.

Knuiman, M.W., Christian, H.E., Divitini, M.L., Foster, S.A., Bull, F.C., Badland, H.M., Giles-Corti, B., 2014. A longitudinal analysis of the influence of the neighborhood built environment on walking for transportation: the RESIDE study. Am. J. Epidemiol. 180 (5), 453–461. https://doi.org/10.1093/aje/kwu171.

Lai, Y., Kontokosta, C.E., 2018. Quantifying place: Analyzing the drivers of pedestrian activity in dense urban environments. Landscape Urban Plann. 180, 166–178. https://doi.org/10.1016/j.landurbplan.2018.08.018.

Le, H.T.K., Buehler, R., Hankey, S., 2018. Correlates of the Built Environment and Active Travel: Evidence from 20 US Metropolitan Areas. Environ. Health Perspect. 126 (7), 077011. https://doi.org/10.1289/EHP3389.

Lee, I.M., Buchner, D.M., 2008. The importance of walking to public health. Med. Sci. Sports Exerc. 40 (7 Suppl), S512–S518. https://doi.org/10.1249/MSS.0b013e31817c65d0.

Lee, S., Sung, H., Woo, A., 2018. The Spatial Variations of Relationship between Built Environment and Pedestrian Volume: Focused on the 2009 Seoul Pedestrian Flow Survey in Korea. J. Asian Architect. Build. Eng. 16 (1), 147–154. https://doi.org/10.3130/jaabe.16.147.

Lee, S., Talen, E., 2014. Measuring Walkability: A Note on Auditing Methods. J. Urban Des. 19 (3), 368–388. https://doi.org/10.1080/13574809.2014.890040.

Lee, S., Yoo, C., Seo, K.W., 2020. Determinant Factors of Pedestrian Volume in Different Land-Use Zones: Combining Space Syntax Metrics with GIS-Based Built-Environment Measures. Sustainability 12 (20), 8647. https://doi.org/10.3390/su12208647.

Lerman, Y., Rofè, Y., Omer, I., 2014. Using Space Syntax to Model Pedestrian Movement in Urban Transportation Planning. Geogr. Anal. 46 (4), 392–410. https://doi.org/10.1111/gean.2014.46.issue-410.1111/gean.12063.

Litman, T.A., 2003. Economic value of walkability. Transp. Res. Rec. 1828 (1), 3–11.

Lo, R.H., 2009. Walkability: what is it? J. Urbanism: Int. Res. Placemaking Urban Sustain. 2 (2), 145–166. https://doi.org/10.1080/17549170903092867.

Long, Y., Thill, J.-C., 2015. Combining smart card data and household travel survey to analyze jobs–housing relationships in Beijing. Comput. Environ. Urban Syst. 53, 19–35. https://doi.org/10.1016/j.compenvurbsys.2015.02.005.

Lu, Y., Xiao, Y., Ye, Y., 2017. Urban density, diversity and design: Is more always better for walking? A study from Hong Kong. Prev Med 103S, S99–S103. https://doi.org/10.1016/j.ypmed.2016.08.042.

Lu, Y., Yang, Y., Sun, G., Gou, Z., 2019. Associations between overhead-view and eye-level urban greenness and cycling behaviors. Cities 88, 10–18. https://doi.org/10.1016/j.cities.2019.01.003.

Lynch, K., 1984. Reconsidering the image of the city. In *Cities of the Mind*. Springer, pp. 151–161.

Manavvi, S., Rajasekar, E., 2021. Evaluating outdoor thermal comfort in "Haats" – The open air markets in a humid subtropical region. Build. Environ. 190, 107527. https://doi.org/10.1016/j.buildenv.2020.107527.

Middleton, J., 2018. The socialities of everyday urban walking and the 'right to the city'. Urban Stud. 55 (2), 296–315. https://doi.org/10.1177/0042098016649325.

Moura, F., Cambra, P., Gonçalves, A.B., 2017. Measuring walkability for distinct pedestrian groups with a participatory assessment method: A case study in Lisbon. Landscape Urban Plann. 157, 282–296. https://doi.org/10.1016/j.landurbplan.2016.07.002.

Murtagh, E.M., Nichols, L., Mohammed, M.A., Holder, R., Nevill, A.M., Murphy, M.H., 2015. The effect of walking on risk factors for cardiovascular disease: an updated systematic review and meta-analysis of randomised control trials. Prev. Med., 72, 34-43. Retrieved from , https://core.ac.uk/download/185482381.pdf.

Neves, A., Brand, C., 2019. Assessing the potential for carbon emissions savings from replacing short car trips with walking and cycling using a mixed GPS-travel diary approach. Transport. Res. Part A: Policy Pract. 123, 130–146.

Panter, J., Griffin, S., Ogilvie, D., 2014. Active commuting and perceptions of the route environment: A longitudinal analysis. Prev. Med. 67, 134–140.

Rzotkiewicz, A., Pearson, A.L., Dougherty, B.V., Shortridge, A., Wilson, N., 2018. Systematic review of the use of Google Street View in health research: major themes, strengths, weaknesses and possibilities for future research. Health & Place 52, 240–246.

Saelens, B.E., Sallis, J.F., Frank, L.D., 2016. Environmental correlates of walking and cycling: Findings from the transportation, urban design, and planning literatures. Ann. Behav. Med. 25 (2), 80–91. https://doi.org/10.1207/S15324796ABM2502_03.

Sallis, J.F., Floyd, M.F., Rodríguez, D.A., Saelens, B.E., 2012. Role of built environments in physical activity, obesity, and cardiovascular disease. Retrieved from Circulation 125 (5), 729–737. https://www.ahajournals.org/doi/pdf/10.1161/CIRCULATIONAHA.110.969022?download=true.

Shannon, C.E., 1948. A Mathematical Theory of Communication. Bell Syst. Tech. J. 27 (3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x.

Steiger, E., Westerholt, R., Resch, B., Zipf, A., 2015. Twitter as an indicator for whereabouts of people? Correlating Twitter with UK census data. Comput. Environ. Urban Syst. 54, 255–265. https://doi.org/10.1016/j.compenvurbsys.2015.09.007.

Sugiyama, T., Leslie, E., Giles-Corti, B., & Owen, N., 2008. Associations of neighbourhood greenness with physical and mental health: do walking, social coherence and local social interaction explain the relationships? J. Epidemiol. Community Health, 62(5), e9-e9.

Sung, H., Lee, S., 2015. Residential built environment and walking activity: Empirical evidence of Jane Jacobs' urban vitality. Transport. Res. Part D: Transp. Environ. 41, 318–329. https://doi.org/10.1016/j.trd.2015.09.009.

Sung, H., Lee, S., Cheon, S., 2015. Operationalizing Jane Jacobs's Urban Design Theory. J. Plann. Educ. Res. 35 (2), 117–130. https://doi.org/10.1177/0739456x14568021.

Talen, E., 1999. Sense of community and neighbourhood form: An assessment of the social doctrine of new urbanism. Urban Stud. 36 (8), 1361–1379.

Wang, S., Shi, C., Fang, C., Feng, K., 2019. Examining the spatial variations of determinants of energy-related CO2 emissions in China at the city level using Geographically Weighted Regression Model. Appl. Energy 235, 95–105.

Wood, L., Frank, L.D., Giles-Corti, B., 2010. Sense of community and its relationship with walking and neighborhood design. Soc. Sci. Med. 70 (9), 1381–1390. https://doi.org/10.1016/j.socscimed.2010.01.021.

Xie, B., Lu, Y., Wu, L., An, Z., 2021. Dose-response effect of a large-scale greenway intervention on physical activities: The first natural experimental study in China. Health Place 67. https://doi.org/10.1016/j.healthplace.2020.102502.

Ye, Y., Zeng, W., Shen, Q., Zhang, X., Lu, Y., 2019. The visual quality of streets: A human-centred continuous measurement based on machine learning algorithms and street view images. Environ. Plann. B: Urban Analyt. City Sci. 46 (8), 1439–1457. https://doi.org/10.1177/2399808319828734.

Yin, L., 2017. Street level urban design qualities for walkability: Combining 2D and 3D GIS measures. Comput. Environ. Urban Syst. 64, 288–296. https://doi.org/10.1016/j.compenvurbsys.2017.04.001.

Yin, L., Cheng, Q., Wang, Z., Shao, Z., 2015. 'Big data' for pedestrian volume: Exploring the use of Google Street View images for pedestrian counts. Appl. Geogr. 63, 337–345. https://doi.org/10.1016/j.apgeog.2015.07.010.

Zang, P., Lu, Y.i., Ma, J., Xie, B.o., Wang, R., Liu, Y.e., 2019. Disentangling residential self-selection from impacts of built environment characteristics on travel behaviors for older adults. Soc. Sci. Med. 238, 112515. https://doi.org/10.1016/j.socscimed.2019.112515.

Zhang, F., Zhou, B., Liu, L., Liu, Y., Fung, H.H., Lin, H., Ratti, C., 2018. Measuring human perceptions of a large-scale urban region using machine learning. Landscape Urban Plann. 180, 148–160. https://doi.org/10.1016/j.landurbplan.2018.08.020.

Zhang, Z., Xiao, Y., Luo, X., Zhou, M., 2020. Urban human activity density spatiotemporal variations and the relationship with geographical factors: An exploratory Baidu heatmaps-based analysis of Wuhan China. Growth and Change 51 (1), 505–529. https://doi.org/10.1111/grow.v51.110.1111/grow.12341.

Zhao, H., Shi, J., Qi, X., Wang, X., Jia, J., 2017. Pyramid Scene Parsing Network. Paper presented at the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR).