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# Building running-friendly cities: effects of streetscapes on running using 9.73 million fitness tracker data in Shanghai, China

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## Abstract

The association between built environment and physical activity has been recognized. However, how and to what extent microscale streetscapes are related to running activity remains underexplored, partly due to the lack of running data in large urban areas. Moreover, few studies have examined the interactive effects of macroscale built environment and microscale streetscapes. This study examines the main and interactive effects of the two-level environments on running intensity, using 9.73 million fitness tracker data from Keep in Shanghai, China. Results of spatial error model showed that: 1) the explanatory power of microscale streetscapes was higher than that of macroscale built environment with  $R^2$  of 0.245 and 0.240, respectively, which is different from the prior finding that  $R^2$  is greater for macroscale built environment than for microscale streetscape; 2) sky and green view indexes were positively associated with running intensity, whereas visual crowdedness had a negative effect; 3) there were negative interactions of land use Herfindahl–Hirschman index with sky and green view indexes, while a positive interaction was observed for visual crowdedness. To conclude, greener, more open and less visually crowded streetscapes, can promote running behavior and enhance the benefits of land use mix as well. The findings highlight the importance of streetscapes in promoting running behavior, instead of a supplement to macroscale built environment.

**Keywords** Street view images, Built environment, Running activity, Deep learning

## Introduction

Sedentary lifestyles and a lack of physical activity pose significant threats to human health, particularly for residents living in urban areas. As a dominant form of physical activity, running can not only promote residents' well-being [1, 2], but also reduces the risks of physical and mental diseases such as obesity and depression [3, 4]. Furthermore, running has emerged as one of the most popular physical activities, with the number of runners consistently increasing and reaching hundreds of millions worldwide [5]. Notably, the number of active runners of fitness tracker app in China reached to 54.70 million in 2022. Therefore, creating a running-friendly city is

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becoming more and more important for residents around the globe.

Understanding the benefits of favorable streetscapes is of great significance. Firstly, streets are widely recognized as one of the key venues for people's running activity, and favorable streetscapes have been reported to effectively promote residents' physical activities such as walking [6, 7], running [8–10], and cycling [11, 12]. Secondly, according to the social-ecological model of physical activity, there are hierarchical needs for human physical activity [13]. That is, neighborhood- and street-level built environments satisfy different activity needs, with streetscapes meeting higher-order demands such as liveliness and aesthetics [13]. Thus, exploring the impacts of neighborhood built environment, combined with those from microscale streetscapes, contributes to a more in-depth understanding of physical activity. Thirdly, compared to neighborhood built environment elements such as the road network, streetscape features are easier and more actionable to modify, particularly in the new Era, thereby benefiting healthy behavior and the health status of urban residents.

However, how and to what extent microscale streetscapes can affect people's running activities have not been well understood. Specifically, among studies examining the impacts of microscale streetscapes, scant attention has been paid to running behavior [9, 14]. Furthermore, among the three types of urban running trails by location, very few studies focus on the street [15, 16]. Moreover, research on the impact of physical activity has predominantly targeted macroscale built environment [15, 17, 18], with microscale streetscapes receiving little attention [6, 19].

To fill the gaps mentioned above, the present study leverages 9.73 million fitness tracker data from Keep, one of China's popular sports-tracking and social platforms, to examine the main and interactive effects of macroscale built environment and microscale streetscape on running intensity in Shanghai, China. Specifically, we address the following research questions: (1) How and to what extent do microscale streetscape features affect running intensity? (2) Can microscale streetscape enhance the positive effect of favorable built environment at macroscale? Our contributions are two-fold. Firstly, we enrich the built environment-associated running studies by simultaneously examining the main and interactive effects of macroscale built environment and microscale streetscape in Chinese cities. Secondly, we demonstrate the applicability of using the crowdsourced big data for running studies in large urban areas.

## Literature review

### Effects of microscale streetscape on running

Some prior studies have indicated that certain features of microscale streetscape can affect running activity. In general, most of running studies concentrate on eye-level greenness [6, 19], and reported that greener and more open streetscapes are more likely to promote running behavior [8, 15, 20], whereas streets that are visually crowded, dense and excessively interrupted have a negative effect [9, 10, 16]. However, such studies are quite limited, making the research question of how and to what extent microscale streetscapes can affect people's running activities have not been well understood.

The insufficient understanding of microscale streetscape effects is partly due to the lack of running data in large urban areas. Traditionally, approaches used to collect running data mainly included field surveys, questionnaires, and running diaries [21–23]. These methods are usually limited by high costs, small samples sizes, as well as limited geographical areas, which may lead to biased results [8, 24]. In response, open crowdsourced fitness tracker data provide great potential to alleviate these limitations. In particular, running data collected from mobile fitness apps, are superior in large data volume, precise GPS-based trajectories, and broad geographic coverages [10, 25].

The limited examination of the impacts of microscale streetscapes, may also stem from the challenges in measuring microscale streetscapes across large spatial areas. Typically, microscale streetscapes are measured through methods such as expert evaluations and respondent surveys [26, 27]. These methods are resource-intensive and time-consuming, but also hard to measure some factors, such as green view index [28]. Recent advances in computer vision techniques represented by deep learning and the increasing available street view images (SVIs), help alleviate these deficiencies. SVIs are superior in large data volume, broad spatial coverage, and low costs in terms of time and money. Computer vision techniques allow for automatic recognition of image content such as trees and walls, which together advances the measurement of microscale streetscapes.

Several recent attempts have used crowdsourced running data and street view images to examine the effects of microscale streetscapes [10, 17, 29]. Particularly, a study using running data from Strava in Boston, USA, found that street environment is significantly associated with the amount of running [8]. This research also highlighted that the collective impact of microscale streetscapes is similar to that of macroscale built environment [8]. Similarly, combining route check-in data from Keep and machine learning approach, a study conducted in Beijing of China indicated significant associations of road running intensity with neighborhood built environment

and microscale streetscapes [9]. However, such studies remain limited.

Apart from the unclear impacts of microscale streetscapes, several efforts and further work are required. Firstly, among studies examining the impacts of microscale streetscapes, most focus on walking and overall physical activity [6, 28, 29], with scant attention paid to running behavior [9, 14], despite its great health benefits and distinct requirements for street environment compared to those of other physical activities. Secondly, among the three types of urban running trails by location, most studies focus on parks and playgrounds [30–32], with fewer addressing streets [15, 16], even though streets are usually more accessible than parks.

Thirdly, research on the impact of physical activity has predominantly focused on macroscale built environment, with microscale streetscapes receiving little attention. Most studies focus on built environment at neighborhood level [15, 17, 18]. Although there is a handful of studies consider microscale streetscapes, they usually concentrate on part of the five-dimension framework of street environment [24], with a particular emphasis on eye-level greenness [6, 19]. Thus, the impacts of other streetscape characteristics such as height-to-width ratio, sky view factor and street furniture [8, 12, 15], have largely not been well understood.

#### **Interactive effects of macroscale built environment and microscale streetscapes**

A large body of studies have indicated the significant associations between built environment and physical activities [10, 23, 29]. However, there are inconsistent findings on the effect of built environment, especially at the neighborhood level [33]. This is partly due to that there may be interactions between multi-level built environments, including the moderation role of microscale streetscapes [12, 29]. Understanding the moderation effect of microscale streetscapes is not only an essential methodological issue in the field of environmental health [34], but also important and instructive for developing effective interventions in built environment, thus to better encourage healthy behaviours.

According to the Ecological Model of Physical Activity, theoretically, one's running behaviour is not only affected by multi-level factors, including the intrapersonal, interpersonal, organizational, community, physical environment and policy levels, but also determined by the interactions among indicators at different levels [34]. Empirically, various moderators affecting the effect of macroscale built environment on physical activity have been explored. These include socioeconomic, demographic and psychosocial factors [34–36], as well as microscale streetscapes [10, 29, 37]. In particular, a Chinese study indicated that there are positive effects of

the interactions between macroscale built environment and streetscape features, particularly the interactive effect between road connectivity and sky view index and building frontage [29]. However, such studies examining the moderation effects of streetscapes are quite limited. It still remains unknown how microscale streetscapes can strengthen or diminish the benefits of favourable built environment to promote physical activity.

## **Materials and methods**

### **Research area**

We examined the main and interactive effects of macroscale built environment and microscale streetscapes on running intensity in Shanghai, China. Shanghai is one of the four first-tier cities in China. As shown in Fig. 1, our research area encompassed the region defined by the Center Ring Highway of the city. The average active users of the Keep app in Shanghai amounted to 4.43 million in 2023, with a total of exercise times reaching approximately 9.73 million in the same year. Moreover, the terrain and climate of the research area selected are conducive, providing favorable conditions for running activities for residents in Shanghai. Therefore, Shanghai was selected for the examination in the present study.

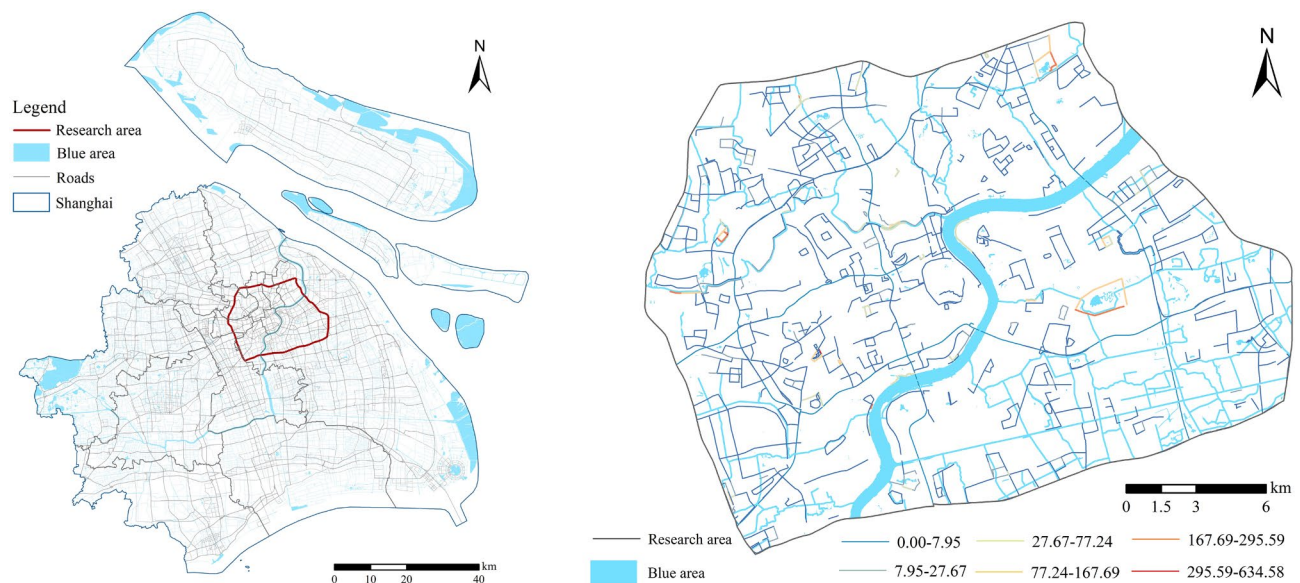
### **Running intensity of street segment**

The variable of running activity is the running intensity of street segment. It is defined as the total times of running for each street segment divided by its length. This definition aligns with the operationalization in prior studies [9–11], aiming to mitigate the issue of potentially higher times of running in longer street segments than shorter ones. At the same time, this study is to understand how and to what extent microscale streetscapes shape residents' running behavior, so street segments intersected by roads were selected as the analysis unit in this work.

Data on running activity were acquired from Keep in September 2023. Similar to Strava, which is popular in Western cities, Keep is among the most utilized sports-tracking and social platforms in China. Its average active users reached 36.40 million per month, with a total of times for exercise approximately hitting 2.10 billion in 2022. In total, we collected 545 running routes with a total of 9.73 million running times within the research area, accounting for 59.08% of the total times of physical activities. Each geo-referenced record of running route includes information on GPS-based route and the number of running times without any personal information. Ultimately, there are totally 882 street segments as analysis samples in the present study.

### **Microscale streetscape indicators**

The measurement of microscale streetscapes was conducted through the framework of urban design qualities



**Fig. 1** Research area (Left) and spatial distributions of running intensity (Right)

at street level [24], which outlines five quality aspects related to people's perceptions and sensations, i.e. imageability, enclosure, scale, transparency, and complexity. For each category, it can be measured through one or more.

This framework is effective in classifying street built environment, since the majority of the significant factors reported in physical activities including running well match the 5Ds categories [8–10]. Hence, the framework has been increasingly used in built environment-associated physical activity studies [38–40]. Table S1 presented the measurement of microscale streetscape in details for this work. Briefly, according to the framework and prior research [28, 38, 41], imageability was usually measured by crowd concentration index and greenery within a street segment. Enclosure was evaluated by sky view factor and building-to-street ratio. Scale was normally measured through public-facility convenience index and non-motorized vehicle interference. Transparency was determined by the proportion of walls on the same side of the street, and street complex was gauged by two factors, i.e. streetscape complexity and visual crowdedness.

These variables of microscale streetscapes were measured through a combination of massive street view images (SVIs) and computer vision technology. As depicted in Fig. 2, SVIs were acquired from the Baidu Street View Image Application Programming Interface (<https://map.baidu.com>). Sampling points were extracted at 50 m intervals, along with road segment acquired from the Baidu Map (<https://map.baidu.com>). Each sampling point featured four street view images at different headings, i.e. 0°, 90°, 180° and 270° (Fig. 2). The size of images

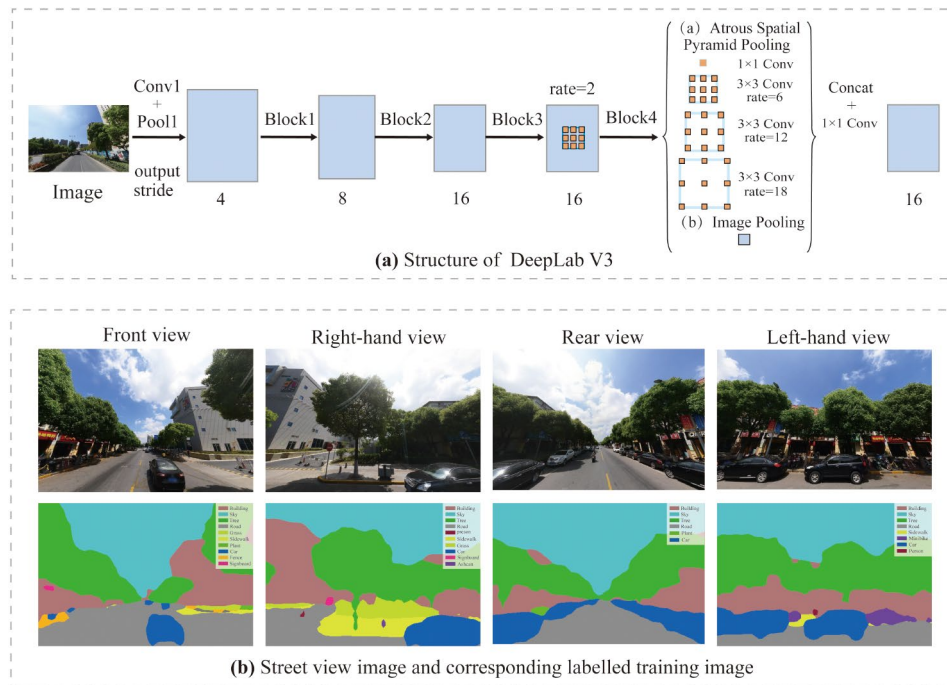
was set to 600×400 pixels. In total, 11,396 points with 45,584 images were collected for this study.

Subsequently, the DeeplabV3 algorithm was used to classify the physical features of Street View Images (SVIs), in combination with the Cityscapes dataset which provides the labels of the objects of cityscapes for each pixel in the SVIs. DeeplabV3, a popular computer vision technique, has been widely used to measure the eye-level features of microscale streetscapes [42, 43], while the Cityscapes dataset is among the most prominent datasets for extracting object classes of cityscapes in urban scenes. As reported, the mean intersection over union and pixel-wise accuracy for semantic segmentation achieved were 82.88% and 84.56%, respectively [44, 45]. Then, the pixel ratio of physical feature for each sampling point, was calculated by averaging the values of pixel ratios from the four images with different headings. Finally, the objective feature for each road segment, was determined by averaging the pixel ratios of sampling points within the same segment. Table S1 details the measurements of microscale streetscape variables, and Fig. 3 illustrates the distributions of several microscale streetscape factors.

### Macroscale built environment indicators

Built environment at the macroscale was measured through the widely recognized 5Ds framework, namely density, diversity, design, destination accessibility, and distance to transit [46]. This framework is effective in measuring built environment at the macroscale, since most of the significant variables reported in health studies are applicable to the 5D categories [8, 9, 23]. Hence, the 5Ds framework has been widely in built environment-associated health studies at the macroscale, particularly





**Fig. 2** Segmentation of street view images to measure streetscape factors

for the neighborhood environment [12, 14, 28]. Table S1 outlined the measurement of macroscale built environment in details for the present study. Briefly, as in many studies [16, 20], a buffer with a radii of 500 m around road segment was established to evaluate macroscale built environment. This buffer size was selected, because it is close to that of blocks in Shanghai [12] and the community–life cycles for 10 min in many Chinese cities [47]. Besides, the 500 m buffer was usually used in prior research, which benefits a comparison of results among different studies [9, 48]. Population density and average building height were utilized to assess density, which represents its two important aspects, i.e. people and building. Design was measured through density of road intersections as well as road connectivity, which characterizes the dimensions of accessibility and connectivity, respectively.

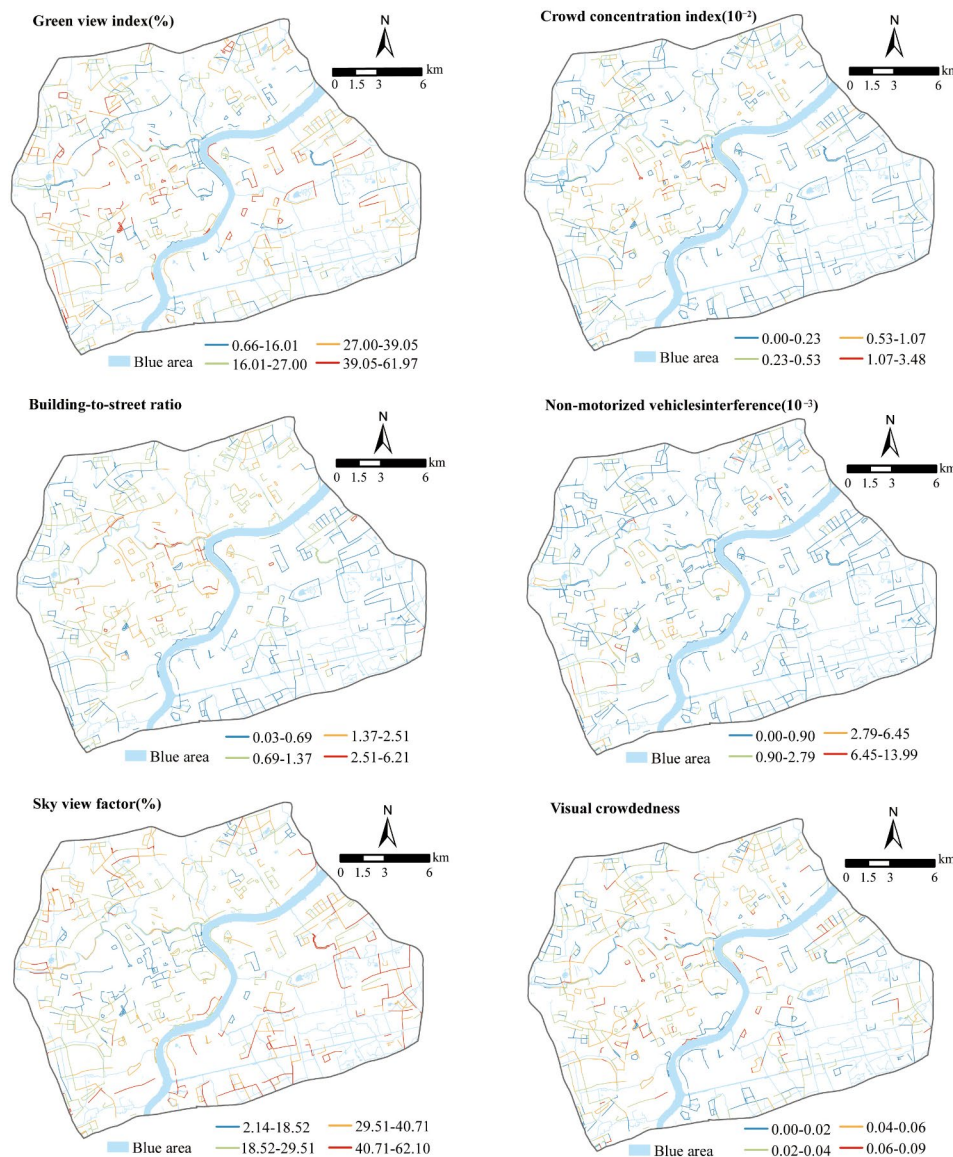
Diversity was evaluated using land use Herfindahl–Hirschman index, i.e. Land use HHI, with values ranging from 0 to 1 [49]. The smaller the value of Land use HHI, the higher mixed degree of different land uses. Destination accessibility was determined by the distance to the nearest park and river. Distance to transit was assessed in terms of proximity to the nearest metro station and density of bus stops. Of the 5Ds variables, population data were acquired from the EasyGo platform (<https://heat.qq.com/bigdata/index.html>), which depicts a real-time spatial distribution of populations. Data on road network and points of interests (POIs), were obtained from the Baidu Maps (<https://map.baidu.com>). Figure 4 shows the

spatial distributions of several built environment factors at macroscale.

**Statistical analysis**

The Variance Inflation Factor (VIF) was computed for both macroscale built environment and microscale streetscape factors to avoid multicollinearity, leaving those with a VIF lower than 10, based on the criterion widely used in many studies [8, 28, 50]. Thus, macroscale built environment included nine factors, i.e. population density and average building height (density), land use HHI (diversity), road connectivity and density of road intersections (design), distance to nearest metro station and density of bus stations (distance to transit), and distance to nearest park and river to evaluate (destination accessibility). For microscale streetscapes, factors comprised crowd concentration index and greenery (imageability), sky view factor and building-to-street ratio (enclosure), public-facility convenience index and non-motorized vehicles interference (scale), streetscape complexity and visual crowdedness (complex), and transparency.

Furthermore, each group of factors, namely macroscale built environment and microscale streetscapes, was separately included in the Ordinary Least Square model (OLS). This is to compare their individual contributions to running behaviour. Subsequently, both groups were combined to evaluate their collective effects on running.

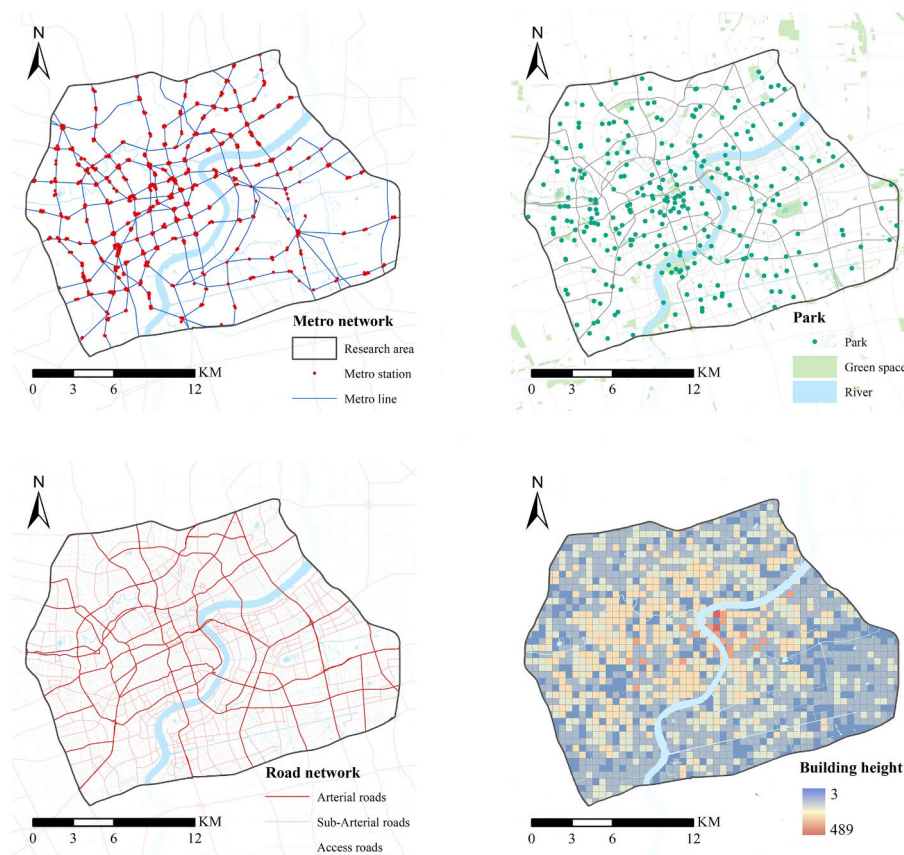


**Fig. 3** Spatial distributions of several microscale streetscape factors

- 1) OLS model 1: Macroscale built environment (MBE) ~ running intensity (dependent variable)
- 2) OLS model 2: Microscale streetscapes (MS) ~ running intensity (dependent variable)
- 3) OLS model 3: MBE + MS ~ running intensity (dependent variable)

Moreover, a spatial autocorrelation model was developed due to the potential of spatial autocorrelation. OLS has been widely used to understand the effect of built environment on healthy behavior, partly due to its superiority in interpretability. As indicated in previous studies [8, 16, 51], however, people’s physical activities, such as walking and running, were influenced by their surrounding neighborhoods and were also spatially autocorrelated.

Hence, Moran’s I was estimated to examine whether spatial autocorrelation exists. If so, the robust Lagrange Multiplier (LM) test was used to determine the type of spatial interaction. Usually, there are three types of spatial effects, i.e. spatial error (SEM), spatial lag (SLM) and both (SAC). In the present study, both Moran’s I and the spatial error effect were significant, which indicated the existence of spatial dependence and the need to use SEM to control the effect of spatial autocorrelation. Similar to the approach with OLS, each of the two groups, i.e. macroscale built environment and microscale streetscapes, was separately added and then combined in the SEM to compare their individual and collective effects on running behavior.



**Fig. 4** Spatial distributions of characteristics of macroscale built environment

- 4) SEM model 1: Macroscale built environment (MBE) ~ running intensity (dependent variable)
- 5) SEM model 2: Microscale streetscapes (MS) ~ running intensity (dependent variable)
- 6) SEM model 3: MBE + MS ~ running intensity (dependent variable)

At last, the interactions between microscale streetscape and macroscale built environment elements were examined through the OLS Model 3 and SEM Model 3, respectively. The two models included the variables of macroscale built environment and microscale streetscape together. This is partly due to the potential interactions between the two-level factors reported in some studies [12, 29, 37]. This is also because the improvement in  $R^2$  was small in the present study, when incorporating both levels of built environment factors in the model simultaneously. We aimed to understand whether favorable microscale streetscapes can enhance the benefits of each of the two macroscale elements, i.e. land use mix and road accessibility. Three microscale streetscape features were targeted, including sky view index, green view index, and visual crowdedness.

## Results

### Descriptive analysis

The summary statistics and Pearson's correlation analysis for running intensity, macroscale built environment and microscale streetscapes, are presented in Table 1; Fig. 5. The standard deviation of running intensity was 41.501 times/km, suggesting a considerable variation in running intensity among runners. Substantial differences were also observed in macroscale built environment and microscale streetscapes. In particular, the standard deviations for green view index, visual crowdedness and sky view factor were 0.122, 1.830 and 0.111, respectively, indicating great variations in microscale streetscape factors. With regards the correlations between the pairwise macroscale built environment and microscale streetscapes, as shown in Fig. 5, most presented low to moderate correlations, with coefficients ranging from  $-0.52$  to  $0.56$ . This further confirmed the absence of multicollinearity between the two-level indicator pairs.



**Table 1** Descriptive statistics of running intensity and two-level built environment elements

Variables	Mean	SD	Min	Median	Max
Running intensity	11.047	41.501	0.001	1.273	634.584
Macroscale built environment					
Population density <sup>a</sup>	1.082	0.482	0.024	1.070	3.030
Average building height	20.831	8.322	3.700	19.233	79.750
Land use HHI <sup>a</sup>	6.970	9.400	0.250	3.710	87.280
Road connectivity	3.414	0.362	2.250	3.393	5.050
Density of road intersections	2.897	0.744	2.000	3.000	4.000
Distance to nearest metro	2.662	1.709	0.010	2.411	8.950
Density of bus stops	0.799	0.639	0.000	0.688	4.880
Distance to nearest park	2.855	1.721	0.000	2.589	10.690
Distance to nearest river	3.023	2.426	0.000	2.656	13.750
Microscale streetscapes					
Green view index	0.243	0.122	0.010	0.233	0.620
Crowd concentration index	0.003	0.003	0.000	0.002	0.030
Sky view factor	0.293	0.111	0.020	0.289	0.620
Building-to-street ratio	0.980	0.701	0.030	0.853	6.210
Public-facility convenience index <sup>a</sup>	0.051	0.076	0.000	0.024	0.875
Non-motorized vehicles interference <sup>a</sup>	0.100	0.170	0.000	0.039	1.399
Street complexity	1.487	3.531	0.030	0.833	58.770
Visual crowdedness <sup>a</sup>	3.159	1.830	0.015	2.902	9.409
Transparency <sup>a</sup>	0.018	0.119	0.000	0.000	2.289

<sup>a</sup> for value=original value/100;

**OLS regression for main effects of macroscale built environment and microscale streetscapes**

Table 2 presents the results of OLS regressions on the main effects of the two-level built environment effects. The F-statistic was significant for macroscale built environment (Model 1), microscale streetscapes (Model 2) and the both (Model 3), suggesting their significant roles in influencing running intensity. Regarding the explanatory power, the R<sup>2</sup> of microscale streetscapes was higher than that of macroscale built environment, with the values of 0.113 and 0.096, respectively. When the two-level built environments were combined in the model, the R<sup>2</sup> improved to 0.186. The majority of macroscale built environment and some of microscale streetscape elements, were significantly associated running intensity. The top three factors for the formal were density of road intersections, distance to the nearest park and land use HHI, with absolute coefficients of 0.458, 0.258 and 0.203, respectively. For microscale streetscapes, the green view

index was the most significant, followed by the sky view index and crowd concentration index, with coefficients of 0.684, 0.465 and 0.255, respectively.

**SEM regression for main effects of macroscale built environment and microscale streetscapes**

The SEM results of the main effects of macroscale built environment, microscale streetscapes and both combined, are shown in Table 3; Fig. 6. In general, there was a considerable increase in the goodness-of-fit for each of the three models upon accounting spatial autocorrelation (spatial error). Specifically, Moran’s I on residuals was significant ( $P < 0.001$ ), with values decreasing from 0.161 to -0.001 for macroscale built environment, from 0.188 to -0.007 for microscale streetscapes, and from 0.162 to -0.005 for both combined (Table 3; Fig. 6). This indicates not only the existence of spatial autocorrelation, but also the effectiveness of SEM in mitigating this issue, as evidenced by Moran’s I close to 0. Regarding the R<sup>2</sup>, it increased from 0.096 to 0.240 for macroscale built environment, from 0.113 to 0.245 for microscale streetscapes, and from 0.186 to 0.314 for the both. Notably, the increase in R<sup>2</sup> was more pronounced for macroscale built environment than microscale streetscapes. This suggests that the SEM model captured more spatial error interaction within the macroscale built environment.

Compared to that of macroscale built environment (R<sup>2</sup>=0.240) and microscale streetscapes (R<sup>2</sup>=0.245), the explanatory power of combining the two group factors, did not show a considerable improvement (R<sup>2</sup>=0.314) in either the OLS or SEM model. This is partly due to the potential of interactions between the two-level factors. With regards to parameter estimates, the magnitudes of many environmental variables shifted significantly, when spatial error interaction was considered. This indicates the potential bias in OLS in the situation of spatial autocorrelation. In particular, the absolute coefficients increased for green view index from 0.741 to 0.796 and for sky view index from 0.318 to 0.391, but decreased for crowd concentration index from 0.221 to 0.190.

**Interactions between macroscale built environment and microscale streetscapes**

Table 4 exhibits the results of the interaction between macroscale built environment and microscale streetscapes. In general, there were significant interactive effects of land use Herfindahl–Hirschman index with sky view index, green view index and visual crowdedness. Specifically, the interactions with the first two streetscape factors were negatively associated with running intensity, whereas a positive interaction was noted with visual crowdedness in either the OLS or SEM model. This indicates that greener, more open and less crowded urban streetscapes, can amplify the benefits of



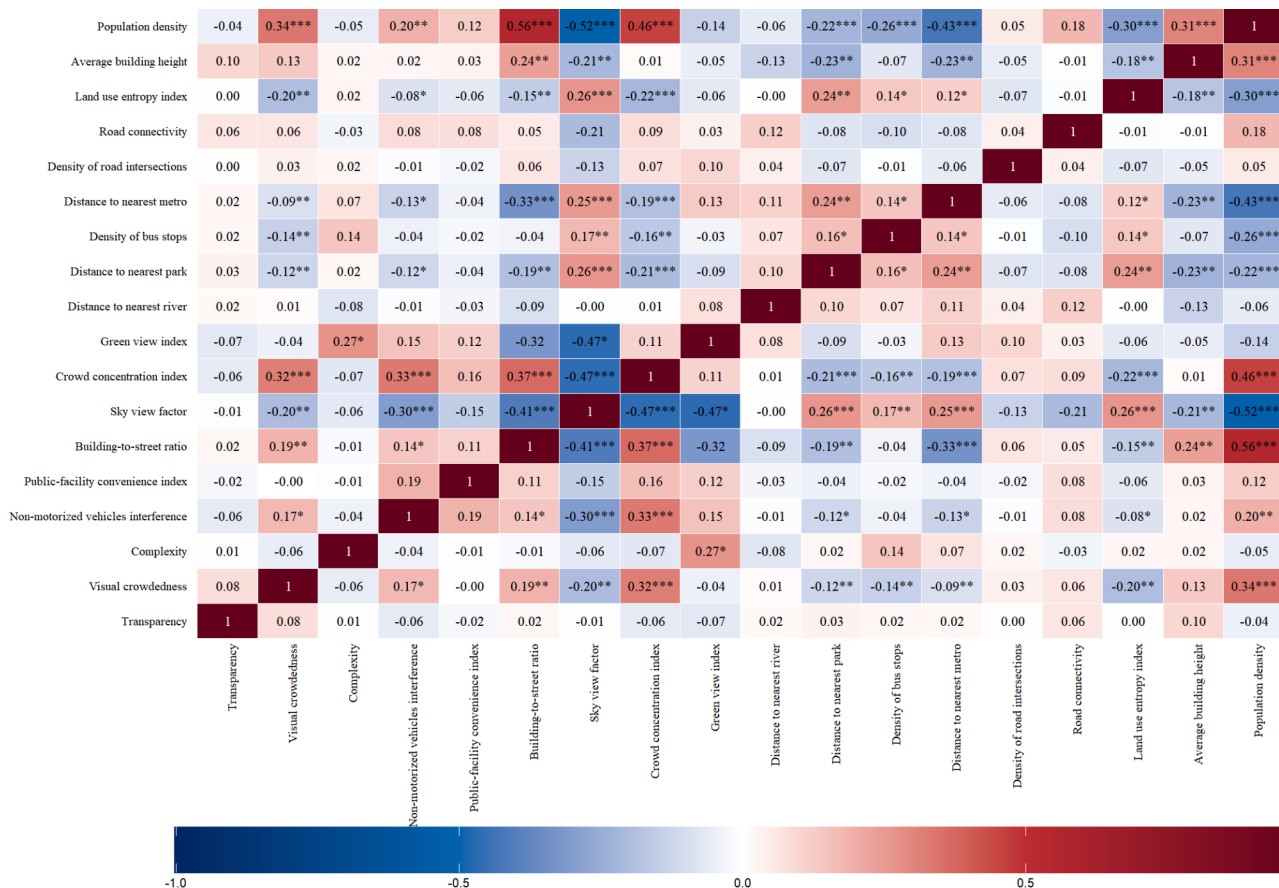


Fig. 5 Pearson's correlation of macroscale built environment and microscale streetscapes; \* for  $P < 0.1$ , \*\* for  $P < 0.05$  and \*\*\* for  $P < 0.01$

land use mix in promoting running intensity. That said, neighborhoods with mixed land use and greener, more open and less crowded streetscapes, are more conducive to running behavior. Moreover, the greatest interaction was observed for sky view index, followed by green view index, and then visual crowdedness, with absolute coefficients of 0.287, 0.238 and 0.161 in the OLS model. A similar pattern of results can be observed in the SEM model. Regarding road accessibility operationalized by density of road intersections, no significant interactions was found for any of the three streetscape factors in neither the OLS nor SEM model.

Regarding the mechanism linking visual crowdedness to running, one potential explanation is that street built environment such as less visual crowdedness, is usually associated with favorable perceptions of safety and comfort [52, 53], which can then, ultimately, promote healthy behavior and status [54–56]. It is reported that mixed land use can encourage physical activity for human beings [8, 28, 33]. Thus, street built environment such as less visual crowdedness, can enhance the benefits of mixed land use to promote physical activity, including running behavior [12, 29]. This argument is also confirmed in the present study. Specifically, there were

negative effects of land use HH and visual crowdedness, but a positive impact was observed for the interaction of the two indicators. This means that neighborhoods with mixed land use and less crowded streetscapes, are more conducive to running behavior.

### Discussions

#### Contributions of macroscale built environment and microscale streetscape features to running intensity

Our findings reveal that the contribution of microscale streetscapes was higher than that of macroscale built environment in explaining running behavior. In our study, the explanatory power of macroscale and microscale groups in SEM regression, reached 0.240 and 0.245, respectively. This finding has two-fold implications. On one hand, it supports the argument that there is a great significance of incorporating microscale streetscapes in interpreting healthy behaviors [9, 28]. In other words, macroscale built environment alone is not sufficient to have an in-depth understanding of the relationship between built environment and physical activity. On the other hand, it underscores the important role of microscale streetscapes in promoting running activity,

**Table 2** OLS regression for the main effects on running intensity

Variables	OLS Model 1		OLS Model 2		OLS Model 3	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Macroscale built environment						
Population density	-0.336**	0.095			0.027	0.113
Average building height	0.153*	0.079			0.202**	0.078
Land use HHI	-0.150*	0.078			-0.203**	0.076
Road connectivity	0.101	0.076			0.117	0.074
Density of road intersections	0.476***	0.075			0.458***	0.072
Distance to nearest metro station	0.127	0.082			0.060	0.079
Density of bus stops	-0.222*	0.090			-0.224*	0.088
Distance to nearest park	-0.301**	0.079			-0.258**	0.076
Distance to nearest river	0.027	0.074			0.023	0.071
Microscale streetscapes						
Green view index			0.741***	0.113	0.684***	0.117
Crowd concentration index			0.016	0.088	0.048	0.089
Sky view factor			0.318**	0.117	0.465**	0.127
Building-to-street ratio			0.041	0.106	-0.060	0.105
Public-facility convenience index			0.049	0.074	0.081	0.072
Non-motorized vehicles interference			0.099	0.078	0.100	0.077
Street complexity			0.133*	0.076	0.152*	0.074
Visual crowdedness			-0.221**	0.077	-0.255**	0.077
Transparency			-0.005	0.073	-0.020*	0.071
Constant	0.156*	0.072	0.156*	0.072	0.156*	0.069
R <sup>2</sup>	0.096		0.113		0.186	
F-statistic	10.251***		12.348***		0.169***	
Moran's I on residuals	0.161***		0.188***		0.162***	
Robust LM (lag)	4.067		8.906		3.155	
Robust LM (error)	24.652***		43.289***		36.772***	

\* for  $P < 0.1$ , \*\* for  $P < 0.05$  and \*\*\* for  $P < 0.01$

instead of a supplement to macroscale built environment as reported in some studies [12, 57].

The finding of the greater explanatory power of microscale streetscape than macroscale built environment in explaining running, is not in line with that of many prior studies [12, 14, 57]. The mechanisms for the greater explanatory power of microscale streetscapes in interpreting running activity are highly complex. There are two potential explanations. One is that eye-level street view images (SVIs) can more accurately represent the actual environment that people experience, feel and sense. Usually, SVIs are taken at pedestrians' perspective, and thus can more accurately capture the complex interactions of street objects that collectively shape one's visual stimuli [28, 58]. However, this is hard for the two-dimensional measurements of macroscale built environment derived using GIS. The second explanation may be that some streetscape factors may serve as proxies for certain built environment elements at macroscale in explaining running behavior, such as green view index acting as the proxy of employment density and intersection density reported in prior studies [28, 57]. This is also evidenced by moderate correlations between macroscale and eye-level factors observed in the present study. For

example, the green view index was significantly associated with population density, land use HHI and distance to the nearest park, with absolute Pearson coefficients of 0.531, 0.243 and 0.235, respectively.

We found that combining macroscale built environment and microscale streetscapes offers better explanatory power ( $R^2$ ) than either group alone, which is in line with the findings from some prior studies [8, 14, 57]. In particular, a London study using the crowdsourced running data from the Strava reported that the  $R^2$  of macroscale built environment and microscale streetscape in explaining running behavior was higher than that of each group alone [57]. The finding suggests the importance of the two-level factors in interpreting running behavior. Macroscale built environment or microscale streetscapes alone, is not sufficient to understand physical activity. However, the improvements in explanatory power are quite limited, with the improved  $R^2$  ranging from 0.069 to 0.073 in SEM regression in the present study. 0.619.

This is partly due to the potential interactions between built environment factors at the same level and across different levels [10, 12, 29]. In the present study, there are significant interactions of land use mix with each of sky view index, visual crowdedness and green view index. We

**Table 3** SEM regression for the main effects on running intensity

Variables	SEM Model 1		SEM Model 2		SEM Model 3	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Macroscale built environment						
Population density	-0.524***	0.127			-0.218	0.133
Average building height	0.241*	0.106			0.255*	0.102
Land use HH	-0.058	0.081			-0.115	0.078
Road connectivity	0.066	0.077			0.076	0.075
Density of road intersections	0.555***	0.069			0.524***	0.067
Distance to nearest metro	0.123	0.088			0.031	0.085
Density of bus stops	-0.177*	0.106			-0.184*	0.102
Distance to nearest park	-0.194*	0.085			-0.166*	0.081
Distance to nearest river	-0.107	0.098			-0.090	0.094
Microscale streetscapes						
Green view index			0.796***	0.118	0.672***	0.119
Crowd concentration index			-0.062	0.084	-0.008	0.083
Sky view factor			0.392**	0.126	0.425**	0.129
Building-to-street ratio			-0.030	0.104	-0.079	0.100
Public-facility convenience index			0.061	0.070	0.100	0.067
Non-motorized vehicles interference			0.082	0.077	0.070	0.074
Complexity			0.147*	0.070	0.164*	0.068
Visual crowdedness			-0.191*	0.074	-0.166*	0.072
Transparency			-0.008	0.065	-0.032	0.063
Constant	0.140	0.176	0.137	0.160	0.145	0.164
R <sup>2</sup>	0.240		0.245		0.314	
Moran's I on residuals	-0.001***		-0.007***		-0.005***	

\* for  $P < 0.1$ , \*\* for  $P < 0.05$  and \*\*\* for  $P < 0.01$

also found higher explanatory power when spatial autocorrelation was controlled, which has also been reported in some prior studies [8, 57, 59]. In particular, the  $R^2$  controlling for spatial interaction was 0.314, higher than that of 0.186 without the control in the present study. The spatial interaction partly relies on that people may be motivated by runners nearby to conduct running activity [8, 51].

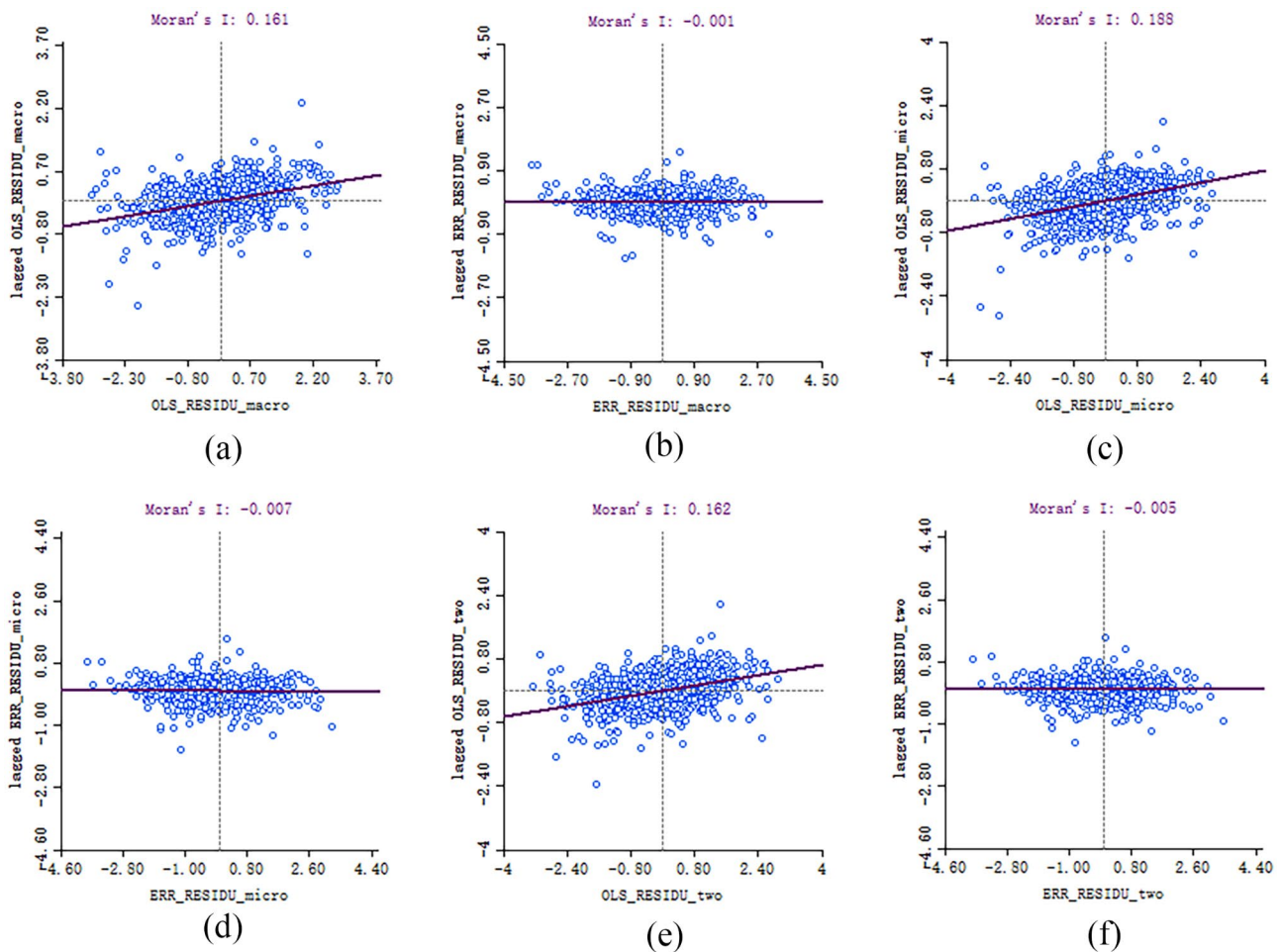
#### Implication for urban design and open space governance

Findings from the present work offer valuable insights for urban design and governance. Firstly, this work indicates the significant and great impacts of microscale streetscapes on running intensity. In particular, apart from high road accessibility and facility accessibility, more open and greener urban streetscapes could increase running intensity, whereas more crowded street environment might hinder running. This highlights that to better promote running behavior, urban design and open space governance should not only focus on the intervention in macroscale built environment [17, 48, 60], but also pay attention to the optimization for microscale streetscapes, particularly the improvement of greenery and open space in urban streets. Moreover, compared to those of macroscale environment, interventions in microscale streetscapes are usually more feasible and cost-effective [8, 28].

Secondly, the findings of macroscale built environment impacts are generally consistent with those from prior studies [9, 23, 24], which demonstrates the potential and applicability of using crowdsourced physical activity data in built environment-physical activity studies in large urban areas. Similar to the widely used Strava in Western cities, Keep is one of the most popular sports-tracking platforms in China. Also, the present study also demonstrated a combination of street view images and deep learning approach to measure microscale streetscapes. Such methodology can be scalable to many cities in the world, thus to better understand the impacts of multi-level and multi-dimension environments on physical activity such as jogging and cycling.

#### Limitations and future work

Several limitations and future research should be well clarified. Firstly, as in many studies [14, 17], our findings may not be applicable to cities with different development patterns, climate conditions and cultural norms, since the present study was conducted in Shanghai, characterized by a high-rise and high-density urban form, as well as a mild and humid climate. If data on multi-city with diverse built environments are available, it would be much more preferable. Secondly, similar to some prior research [9–11], the use of road segment as analysis unit to allocate running data in large urban areas, leads



**Fig. 6** Moran's I on residuals of OLS and SEM for macroscale built environment, microscale streetscapes and the both

to a lack of control of individual characteristics, such as socioeconomic and healthy behavior factors, which is likely to bias our findings. Thirdly, Keep users tend to be young, with aged under 30 years old accounting for around 70%, limiting the generalizability of our findings to other population groups.

Fourthly, the mechanisms linking microscale streetscapes to physical activity can be further explored. The aim of the present study is to indicate the significance of including microscale streetscapes in explaining running activity, instead of examining their causal relationships, due to the complexity of factors that may confound such associations [14, 28, 59]. Thus, how built environment, particularly those at microscale such as streetscapes, affects physical activity can be further understood, including environmental perceptions such as safety and aesthetics [24, 60, 61], which can provide theoretical foundations for environmental health studies.

### Conclusions

Microscale streetscapes significantly influence running intensity, with greener and more open streetscapes promoting running behavior, whereas streets with high visual crowdedness may inhibit it. The contribution of microscale streetscapes in explaining running intensity, was higher than that of macroscale built environment. In addition, more open, greener, and less crowded streetscapes, can enhance the benefits of land use mix in promoting running activity. To our knowledge, this is one of the few studies using crowdsourced running big data in large urban areas, to simultaneously explore the effects of macroscale built environment and microscale streetscapes in Chinese cities. The findings underscores the significance of streetscapes in encouraging healthy lifestyles, instead of a supplement to macroscale built environment.



**Table 4** Interactions between macroscale built environment and microscale streetscapes

Variables	OLS		SEM	
	Coef.	S.E.	Coef.	S.E.
Macroscale built environment				
Population density	-0.257*	0.132	-0.056	0.114
Average building height	0.246*	0.100	0.205**	0.077
Land use HHI	0.053	0.086	-0.012	0.086
Road connectivity	0.064	0.075	0.113	0.074
Density of road intersections	0.533***	0.066	0.472***	0.072
Distance to nearest metro	0.046	0.084	0.075	0.079
Density of bus stops	-0.169*	0.101	-0.215*	0.088
Distance to nearest park	-0.146*	0.080	-0.255**	0.075
Distance to nearest river	-0.081	0.092	0.004	0.071
Microscale streetscapes				
Green view index (GVI)	0.657***	0.117	0.634***	0.116
Crowd concentration index	-0.030	0.083	0.044	0.088
Sky view factor (SVF)	0.400**	0.127	0.439**	0.127
Building-to-street ratio	-0.052	0.099	-0.032	0.104
Public-facility convenience index	0.080	0.067	0.070	0.071
Non-motorized vehicles interference	0.055	0.073	0.072	0.076
Street complexity	0.161*	0.067	0.160*	0.073
Visual crowdedness (VC)	-0.141*	0.073	-0.215**	0.078
Transparency	-0.035	0.062	-0.029	0.070
Interactions				
Land use HH × GVI	-0.238**	0.086	-0.242*	0.095
Land use HH × SVF	-0.287**	0.089	-0.306**	0.097
Land use HH × VC	0.161*	0.090	0.162*	0.099
Density of road intersections × GVI	0.044	0.070	0.083	0.076
Density of road intersections × SVF	0.075	0.071	0.085	0.077
Density of road intersections × VC	-0.068	0.064	-0.164*	0.071
Constant	0.252	0.162	0.264**	0.073
R <sup>2</sup>	0.332		0.214	

\* for  $P < 0.1$ , \*\* for  $P < 0.05$  and \*\*\* for  $P < 0.01$

### Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s12889-024-19605-4>.

Supplementary Material 1

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### Author contributions

Conceptualization, Huagui Guo and Jiang Liu; Methodology, Huagui Guo and Shuyu Zhang; Software, Yufei Liu and Runrong Lin; Validation, Huagui Guo, Shuyu Zhang and Jiang Liu; Formal analysis, Shuyu Zhang and Yufei Liu; Data curation, Yufei Liu and Runrong Lin; Writing – original draft, Huagui Guo and Shuyu Zhang; Writing – review & editing, Jiang Liu; Supervision, Huagui Guo and Jiang Liu; Funding acquisition, Huagui Guo. All authors reviewed the manuscript.

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### Data availability

No datasets were generated or analysed during the current study.

### Declarations

#### Ethics approval and consent to participate

Not applicable.

#### Consent for publication

Not applicable.

#### Competing interests

The authors declare no competing interests.

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