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# Built environments and obesity: A framework considering residences, commute routes, and workplaces

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ABSTRACT

The built environment is a significant contributor to obesity, but previous studies have focused more on the built environment at residential areas, ignoring that at other geographical contexts. This study introduces an innovative framework to explore the relationships between the built environment at various geographic contexts and obesity, including residences, commuting routes, and workplaces. Based on a sample consisting of 1043 adults in Shanghai, the gradient boosting decision trees model is employed to examine how built environments around residences, commuting routes, and workplaces affect obesity, controlling for sociodemographics and air pollutants. Results show that the built environment around commuting routes makes the largest contributions to obesity, accounting for 21 %. Built environments around workplaces and residences have similar contributions to obesity, each accounted for 16 %. Moreover, some built environment elements around commuting routes and residences (population density, restaurant density, and intersection density) have similar and positive correlations with obesity. Residential and workplace transit stop densities have different associations with obesity, which are U-shaped and negative, respectively. Additionally, greenspace around commuting routes, $PM_{2.5}$ and mixed land use surrounding workplaces, and $NO_2$ surrounding residences are positively related to obesity. These findings encourage urban planners to meticulously optimize and design the built environment for reducing obesity and bolstering healthy cities.

## 1. Introduction

Obesity significantly increases risks for numerous diseases, such as cardiovascular diseases and mental disorders. 16 % of adults worldwide have been obese and the number of obese population is still growing (WHO, 2024). In China, the obesity rate was 14 % in 2019 (Chen et al., 2023a), leading to heavy healthcare burdens (Zeng et al., 2021). Hence, reducing obesity has become a key target to achieve the Sustainable Development Goal 3 for ensuring healthy lives and well-being for all ages (Ralston et al., 2021).

The built environment plays a critical role as an upstream factor influencing obesity (Sallis et al., 2012; Swinburn et al., 2011; Yin et al., 2024c; Zhang et al., 2019). A well-planned urban layout characterized by high density, high diversity, good design, high destination and transit accessibility, can improve access to health-promoting resources such as healthy food outlets and fitness facilities, resulting in a lower risk of being obese (De Nazelle et al., 2009; Garfinkel-Castro et al., 2017; Pearson et al., 2014). Emerging studies further indicate that the collective contribution of the built environment on obesity may surpass that of sociodemographic and behavioral determinants (Wang et al., 2021; Yin et al., 2020).

However, previous studies have concentrated on the built environment at residential areas, overlooking the environmental exposure around commuting routes and workplace neighborhoods. The commuting environment, as an essential component of daily exposure, plays an important role in influencing obesity, including residences (i.e., origins), routes, and workplaces (i.e., destinations). Focusing solely on the residential built environment while neglecting individual mobility-based exposures may misestimate the overall relative importance of the built environment, leading to the neighborhood effect averaging

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problem (Kwan, 2018b). For example, people's daily behaviors (e.g., eating, physical activity, travel, and social interaction) mediate the association between the built environment and obesity (Frank et al., 2019), but these behaviors vary across different spatial contexts. Evidence from Shanghai suggests that individuals spend more time engaging in leisure physical activity in their residential neighborhoods (Yin et al., 2023c), while having more social interactions in their workplace neighborhoods (Yin et al., 2024a). Therefore, the relative importance of the built environment around residences and workplaces in relation to obesity may differ. Moreover, a recent study has suggested that green spaces along people's travel routes are positively associated with people's life satisfaction by increasing their travel satisfaction (Sun et al., 2024). Considering that both daily activities and life satisfaction are linked to obesity (Wadsworth & Pendergast, 2014), the environmental exposure surrounding commuting routes may also be an important contributor to obesity. Therefore, it is necessary to develop a comprehensive framework based on daily commuting, which allows for the exploration of how the built environment across various spatial contexts affects obesity, providing innovative findings to the literature. Moreover, understanding which of these environmental factors most profoundly impacts obesity can guide urban planners to create environments that more effectively mitigate obesity.

Moreover, the built environment surrounding residences, routes, and workplaces may be associated with obesity differently. The second law of geography highlights that geographical attributes exhibit uncontrolled variance in space, which is also called spatial heterogeneity (Goodchild, 2004). In other words, the built environment around residences may present different impacts on obesity compared to that around routes and workplaces. On the one hand, people's daily activities are jointly determined by the built environment across different spatial contexts (Kwan, 2018). For example, although there are many transit stops around residences, people cannot commute by transit if there is no transit stop around workplaces, resulting in less active travel and higher risks of being obese. Transit stops around commuting routes may not directly influence travel behavior because people often choose travel modes based on the built environment around origins and destinations. However, it can affect people's commuting experience by the passenger flow and convenience of transfer, indirectly affecting mode choice and obesity. On the other hand, people's demands to the built environment are various in different spatial contexts (Sun et al., 2022a). For example, people often prefer to live in quiet neighborhoods, thereby mixed land use around residences may result in a lower life satisfaction due to crowdedness and noise. However, people prefer to work in busy neighborhoods, and hence, mixed land use around workplaces leads to higher life satisfaction since it provides various travel destinations (Yin et al., 2024a). These opposite associations are also found between mixed land use and leisure physical activity around residences and workplaces (Yin et al., 2023c). These studies underscore the importance of spatial contexts, suggesting that the effects of the built environment may not be generalized across all spatial contexts. Hence, it is necessary to examine whether the associations between built environment and obesity differ across different contexts.

In recent years, increasing attention has been given to the nonlinear influence of the built environment on obesity, though consensus on these nonlinear patterns and the key thresholds remains elusive. For example, research using the UK Biobank dataset suggests a reserved U-shaped relationship between residential density and obesity (Sarkar et al., 2017), while studies from China indicate a U-shaped association, but the precise thresholds remain uncertain (Chen et al., 2023b; Sarkar et al., 2017; Yin et al., 2020). Consequently, further studies are needed to define the effective thresholds for built environmental elements, which are essential for advancing the understanding of the complex nexus of built environment factors with obesity, as well as for informing the planning of healthier cities.

Overall, three significant research gaps have been identified in the current literature. First, there is a noticeable absence of a comprehensive framework that simultaneously involves residences, commuting routes, and workplaces when exploring the connection between built environments and obesity. Second, it remains uncertain whether environmental factors within different spatial contexts exert consistent effects on obesity. Third, existing studies have not adequately addressed the nonlinear influence of environmental variables on obesity. To bridge these gaps, we raise three research questions. First, what is the relative importance of the built environment surrounding residences, commuting routes, and workplaces to obesity, respectively? Second, do built environments in various spatial contexts exhibit consistent or divergent associations with obesity? Third, are there nonlinear relationships of the built environment with obesity; and if so, what are the specific thresholds? Answering these questions could contribute valuable insights into the nexus of the built environment in different spatial contexts with obesity, thereby supporting the development of more targeted and effective strategies for obesity prevention and management.

We propose a conceptual framework for this study (Fig. 1), which suggests that obesity is influenced by the built environment in a nonlinear manner, particularly in the areas surrounding the origins (residences), commuting routes, and destinations (workplaces), adjusted by commuting attributes, sociodemographic factors, and air pollutants. To examine this framework and answer the research questions, we employ a machine learning approach to a sample from Shanghai, to investigate the linkage between obesity and the built environment surrounding residential neighborhoods, commuting routes, and workplace neighborhoods.

## 2. Method

### 2.1. Data

As of 2021, Shanghai, one of China's most populous and developed cities, spans an area of 6341 km$^2$, with a total population of around 25 million. The obesity rate was approximately 9.8 % in Shanghai in 2019 (Guo et al., 2019). The present study utilized data from the Built Environment and Residents' Behavior Survey, collected between August 2018 and February 2019 based on a stratified, multistage, and probability-proportional-to-size sampling method (Sun et al., 2022a). First, it divided the built-up area of Shanghai into 10 parts according to administrative divisions. Then, it randomly selected 20 % of the subdistricts within each part, resulting in a total of 30 subdistricts. Subsequently, it randomly chose one neighborhood within each selected subdistrict, with additional three neighborhoods included to account for neighborhoods with small populations, yielding 33 neighborhoods in total. Last, it randomly selected 35 households within each neighborhood. Eligible participants included household heads or their spouses aged 18 to 60 years, who had resided in the selected neighborhood and had been employed at a fixed workplace for at least six months. Skilled investigators conducted face-to-face interviewers with participants in their homes to collect information about their workplace locations, commuting behavior, health status, and sociodemographic attributes. The investigators employed Amap to generate the shortest commuting routes from residences to workplaces, and adjusted the routes after double checking with the participants. We mapped the commuting routes using ArcGIS 10.7. Participants were excluded if they had missing information on their height or weight, and the final sample consisted of 1043 respondents (Fig. 2). The response rate was approximately 50 %. This survey was approved by the Ethics Board of East China Normal University (HR080-2021) and the detailed introduction of this survey can be found elsewhere (Chen et al., 2024; Yin et al., 2024a).

### 2.2. Variables

The response variable was the presence of obesity, measured by body mass index (BMI) of 28 kg/m$^2$ or higher (Pan et al., 2021). BMI is

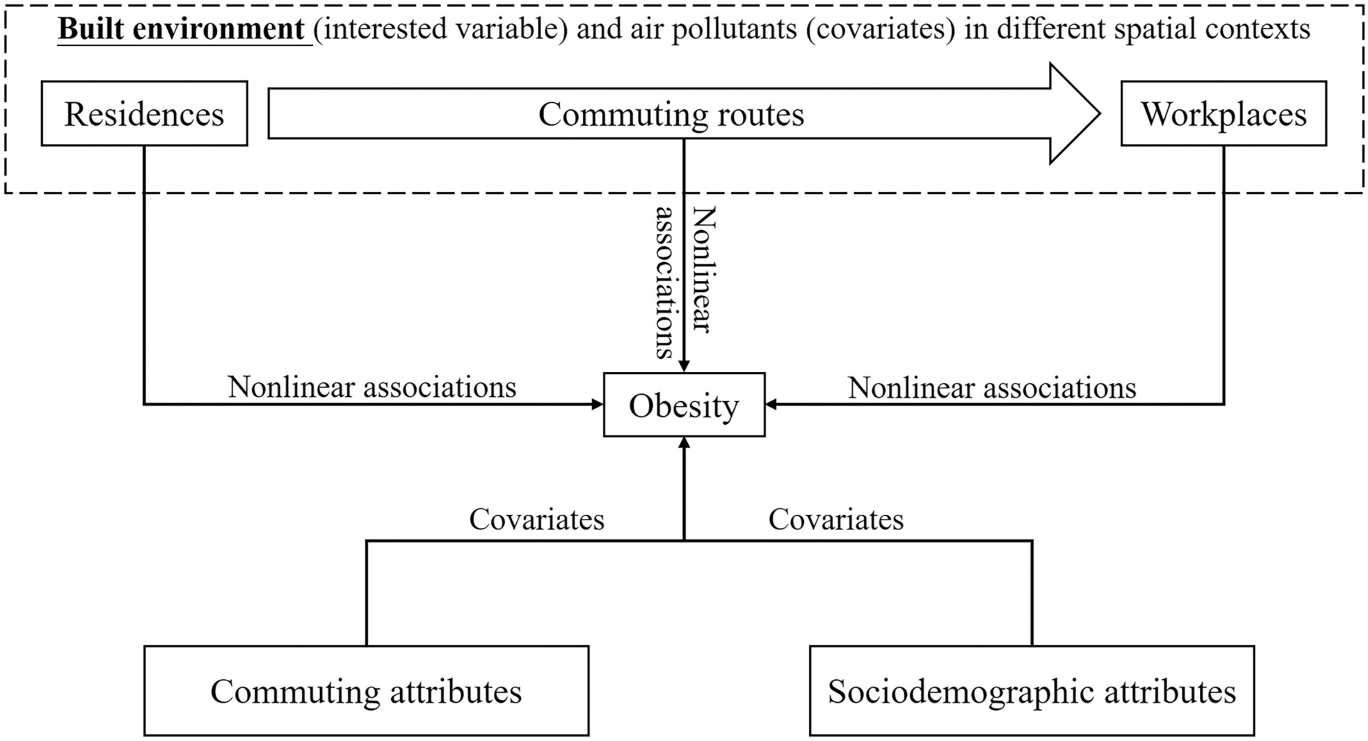


**Fig. 1.** A conceptual framework of the association between the built environment from commuting origins to destinations and obesity.

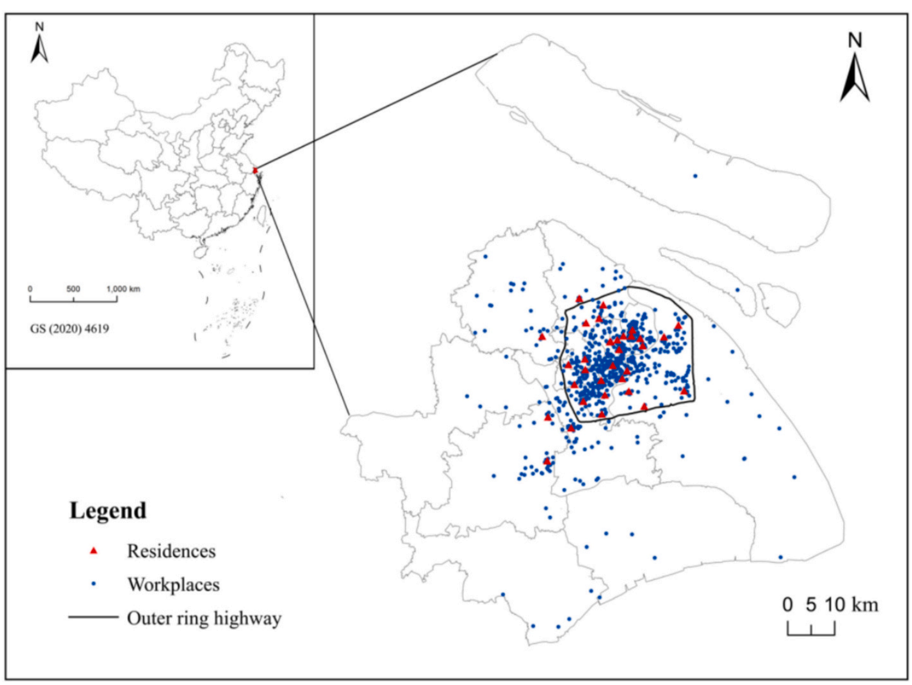


**Fig. 2.** Sample distributions.

calculated by dividing an individual's weight by the square of her/his height (kg/m$^2$) (Gu et al., 2006).

The built environment and air pollutants were measured in three spatial contexts, which were residences, commuting routes, and workplaces. 400-m road network buffers were used to capture the environmental variables around residences and workplaces. This is typically assumed that a 5-min walking distance and commonly used in the literature (Foda & Osman, 2010; Palomino & Carrascal, 2007). 50-m road network buffers were used to capture the environmental variables around commuting routes, in line with the literature (Tamura et al., 2019; Zhang & Mu, 2020).

Based on the framework of the compact built environment and chronic diseases (Ewing et al., 2014; Frank et al., 2019), the built environment in this study was measured by population density, land use diversity, intersection density, transit stop density, and green space, which were mainly related to energy expenditure. We also measured the restaurant density to reflect the built environment related to energy intake following the literature (Romieu et al., 2017; Yin et al., 2023a). Within a buffer, we used the population size divided by the buffer area to define population density, using data from the 2018 WorldPop dataset (https://www.worldpop.org/). Land use diversity was calculated using land use entropy index, considering the areas of 12 urban land use categories (e.g., administration, public services, commercial and service facilities, utilities, etc.) based on essential urban land use categories in 2018 China (Dai et al., 2020; Gong et al., 2020). The densities of intersections, transit stops, and restaurants were calculated by dividing their respective counts by the buffer size, using data from the Amap in 2018 (https://lbs.amap.com/). The extent of green spaces was quantified by measuring the area of green land within each buffer based on the area of interest data extracted from 2018 Amap (https://lbs.amap.com/). Additionally, the average concentrations of six key air pollutants ($PM_{2.5}$, $PM_{10}$, $NO_2$, $SO_2$, $O_3$, CO) within each buffer were sourced from the China High Air Pollutants in 2018, with $PM_{10}$ being excluded from the model due to multicollinearity.

We controlled commuting behavior in the model because it was related to both the environmental variables and personal obese status. The measurement of commuting distance was established by calculating the shortest distance via street networks from the residence to the workplace. The commuting mode was a categorical variable, including car, bus, subway, e-bike, cycling, and walking. Commuting duration indicated the total duration spent from the residence to the workplace.

Sociodemographic predictors were included as covariates in the model and comprised sex (male/female), age (continuous variable), hukou status (Shanghai hukou vs others), years of education (continuous variable), marital status (married/others), household size (continuous variable), household annual income (continuous variable, in CNY 10,000), and number of children (continuous variable).

### 2.3. Analysis approach

We utilized gradient boosting decision trees (GBDT) to model the relationship between environmental attributes and obesity across various contexts, including residences, workplaces, and commuting routes. GBDT integrates decision trees with a gradient boosting method. The process begins by categorizing observations into multiple regions based on binary responses, and then predicting the outcome using the mean of observations within each region (Ma et al., 2018). Subsequent trees are constructed iteratively, with each new tree predicting the residuals of the previous ones until no further improvement is achieved (Chen & Liu, 2021). A detailed introduction to the GBDT algorithm is provided by Tao et al. (2020).

Compared to traditional linear regression models, GBDT has some strengths. First, GBDT effectively models complex nonlinear relationships between predictors and the outcome without the requirement for linear assumptions (Hu et al., 2023). Second, it enhances prediction accuracy by allowing for fewer constraints and considering interactions among predictors (Chen & Liu, 2021; Yin et al., 2020). Third, GBDT is robust with smaller sample sizes and can handle missing data well (Liao et al., 2022; Seto et al., 2022). Moreover, compared to other machine learning models, such as random forests and extreme gradient boosting decision trees, GBDT often has better model performance (Liang et al., 2020). Thus, GBDT has been increasingly adopted in exploring the nexus between the built environment and health behavior (Liu et al., 2021a; Yang et al., 2022).

The statistical analysis was conducted using the "gbm" package in R software (Greenwell et al., 2020), with the Bernoulli function applied for predicting obesity. We used a grid search approach combined with a fivefold cross-validation procedure to select the best tree depth from 1 to 49 and the best number of trees from 1 to 5000. A learning rate of 0.001 was set to fine-tune the model's performance and accuracy. We identified the optimal model when the tree depth was 2 with 1886 trees. Hence, we set the tree depth to 2 and the number of trees to 2000 trees to ensure that the optimal tree model could be found.

Relative importance and accumulated local effects plots were used to report the results of GBDT. The former reflected each predictor's importance in minimizing squared loss compared to others, where a higher relative importance suggested stronger predictive power (Friedman, 2001). The latter visualized the marginal effect of predictors on the response and were robust to data with multicollinearity, illustrating nonlinear and threshold effects of environmental factors (Molnar, 2020; Tao & Cao, 2022). Additionally, the nonlinear associations were smoothed with a degree of 0.6, which is a tradeoff between overfitting and oversmoothing (Yin et al., 2020), suggesting that 60 % of weight is placed on nearby data points in each local smoothing operation.

## 3. Results

### 3.1. Sample description

Table 1 presents the response and personal variables. In our sample, 5 % of respondents were obese, which was slightly lower than that the obesity rate (6–10 %) reported in other studies in Shanghai (Guo et al., 2019; Hou et al., 2008). The possible reason is that our sample included employed individuals and was collected in the built-up area of Shanghai, which often had lower risks of being obese (Pan et al., 2021).

Males made up 46 % of the respondents, with an average age of 39.5 years. The respondents were 77 % married and Shanghai hukou holders. Respondents achieved about 14 years of education on average. A respondent's household consisted of three people including one child, and the household annual income was approximately CNY 181,100 on average. Overall, our sample had higher income and education levels than the general population in Shanghai, primarily because it comprised employees aged 18–60 years living in built-up areas. However, this was unlikely to significantly affect the conditional association of the built environment with obesity, as the multivariable analysis controlled for covariates with sufficient variance among respondents (Yin et al., 2023b). Regarding commuting attributes, respondents' mean commuting distance was 7.96 km. The majority of respondents

**Table 1**
Personal characteristics.

| Variables | Mean (SD)/% |
|---|---|
| Obesity | |
| Yes | 5 % |
| No | 95 % |
| Sociodemographics | |
| Sex | |
| Male | 46 % |
| Female | 54 % |
| Age (years) | 39.51 (10.22) |
| Shanghai hukou | |
| Yes | 77 % |
| No | 23 % |
| Education (years) | 13.98 (2.56) |
| Married | |
| Yes | 77 % |
| No | 23 % |
| Household size (count) | 2.95 (1.02) |
| Household income (CNY 10,000) | 18.11 (12.20) |
| Children (count) | 0.81 (0.60) |
| Commuting attributes | |
| Commuting mode | |
| Car | 13 % |
| Bus | 18 % |
| Subway | 29 % |
| E-bike | 16 % |
| Bike | 6 % |
| Walk | 19 % |
| Commuting distance (km) | 7.96 (9.40) |
| Commuting duration (min) | 43.14 (33.60) |

commuted by subway (29 %), followed by walking (19 %), bus (18 %), and e-bike (16 %). The mean commuting duration was 43 min.

Table 2 elucidates the characteristics of environmental variables. On average, workplaces had higher population density, higher levels of mixed land use, intersection density, and transit stop density. Restaurant density around commuting routes was higher than that around residences and workplaces. Green space and the concentration of air pollutants were similar around residences, workplaces, and commuting routes on average. Moreover, the mean value of variance inflation factors was 3.42 and each predictor had a value below 10, suggesting that multicollinearity might not substantially bias the subsequent analysis.

### 3.2. Relative importance

Table 3 illustrates the relative contributions made by predictors to obesity, with the total contribution of all predictors scaled to 100 %. Collectively, environmental characteristics made approximately 69 % of the total contributions to predicting obesity. The environment around commuting routes emerged as the most important contributor (26 %), surpassing that around workplaces (23 %) and residences (20 %). Moreover, the built environment around commuting routes claimed the highest relative importance at 21 %, overshadowing workplaces (16 %) and residences (16 %). However, air pollutants contributed to predicting obesity less than half as much as the built environment. Air pollutants around workplaces (7 %) made a larger contribution to predicting obesity than those around commuting routes (5 %) and residences (5 %).

Regarding the individual environmental predictor, around commuting routes, population density was the most important predictor to obesity (7 %), which was also the fourth important predictor among all the variables, followed by restaurant density (5 %), intersection density (4 %), and area of green spaces (3 %). Around workplaces, land use diversity was the most important predictor (8 %), which was also the third important variable among all the predictors, followed by $PM_{2.5}$ (4 %), restaurant density (3 %) and transit stop density (2 %). Around residences, transit stop density was the most important built environmental predictor (5 %), followed by intersection density (4 %), population density (4 %), $NO_2$ (3 %), and restaurant density (3 %). Each of the other predictors made negligible contributions to BMI, all smaller than 2 %.

Personal attributes collectively made 31 % contributions to predicting obesity. Commuting attributes (24 %) were more important than sociodemographics (7 %). Among all the predictors, commuting mode emerged as the single most impactful predictor among all personal attributes, with a remarkable contribution of 12 %. Commuting distance followed closely, accounting for 11 % of the predictive power. However, commuting duration only had a limited contribution to obesity. Among sociodemographic attributes, only age and sex demonstrated contributions greater than 2 % to predicting obesity, ranking 15th and 17th, respectively.

**Table 2**
Characteristics of environmental variables.

| Variables | Mean (SD) | | |
|---|---|---|---|
| | Residence | Workplace | Commuting route |
| Built environment | | | |
| Population density (10,000/km$^2$) | 2.04 (1.32) | 2.36 (1.84) | 2.21 (1.28) |
| Land use diversity | 0.57 (0.32) | 0.61 (0.31) | 0.55 (0.28) |
| Intersection density (count/km$^2$) | 80.72 (137.77) | 84.13 (100.71) | 64.97 (79.82) |
| Transit stop density (count/km$^2$) | 12.77 (7.09) | 14.52 (9.52) | 9.83 (9.68) |
| Restaurant density (count/km$^2$) | 41.20 (34.23) | 54.37 (58.35) | 66.87 (73.57) |
| Area of green space (km$^2$) | 0.02 (0.03) | 0.03 (0.05) | 0.03 (0.05) |
| Air pollutants | | | |
| $PM_{2.5}$ (μg/m$^3$) | 35.36 (0.72) | 35.38 (0.95) | 35.40 (0.70) |
| $NO_2$ (μg/m$^3$) | 42.52 (1.75) | 42.06 (3.39) | 42.45 (1.75) |
| $SO_2$ (μg/m$^3$) | 10.41 (0.57) | 10.31 (0.89) | 10.38 (0.55) |
| $O_3$ (μg/m$^3$) | 103.09 (1.39) | 101.85 (9.65) | 102.80 (2.47) |
| CO (mg/m$^3$) | 0.68 (0.02) | 0.68 (0.05) | 0.68 (0.02) |

Note: $PM_{2.5}$ means particulate matter with a diameter of 2.5 μm or smaller; $NO_2$ means nitrogen dioxide; $SO_2$ means sulfur dioxide; $O_3$ means ozone; CO means carbon monoxide.

### 3.3. Nonlinear associations between the environment and obesity

We present the nonlinear impacts of environmental variables with relative importance greater than 2 % in this section. The association of other built environmental and air pollution variables with obesity can be found in Appendix Figs. SM1 and SM2. Fig. 3 illustrates the nonlinear associations between key environmental variables around commuting routes and obesity. Population density beyond 17,000 people/km$^2$ exhibited a positive correlation with obesity. Restaurant density within the range from 90 to 250 counts/km$^2$ had a positive correlation with obesity. Intersection density below 175 counts/km$^2$ had a positive correlation with obesity. The area of green spaces demonstrated a slight positive correlation with obesity within a narrow range of 0.035 to 0.04 km$^2$. Outside this range, the effects of these predictors on obesity were minimal.

Fig. 4 illustrates the nonlinear correlations between key environmental variables surrounding workplaces and obesity. Land use diversity was positively correlated with obesity once it surpassed a threshold of 0.9. Below this threshold, its contribution to obesity was negligible. Restaurant density showed an almost static relationship with obesity. Transit stop density revealed a protective effect against obesity when it ranged from 2 to 8 stops/km$^2$. Outside of this range, its association with obesity appeared to be negligible. $PM_{2.5}$ levels greater than 35.5 μg/m$^3$ showed a positive association with obesity.

Fig. 5 illustrates the complex relationships between key environmental factors and obesity around residences. Specifically, transit stop density exhibited a U-shaped relationship with obesity. A density below 5 stops/km$^2$ was linked to a lower likelihood of obesity, while a density between 15 and 20 stops/km$^2$ was positively associated with obesity. Outside of this range, transit stop density exhibited a trivial association with obesity. Intersection density revealed a positive association with obesity in general. Population density demonstrated a significant positive relationship when exceeding 25,000 people/km$^2$. Restaurant density exhibited a positive correlation with obesity within a range of 50 to 110 restaurants/km$^2$. The concentration of $NO_2$ between 41.5 and 42.5 μg/m$^3$ demonstrated a slightly positive association with obesity.

### 3.4. Nonlinear associations between key personal variables and obesity

Fig. 6 shows the association between key commuting variables and obesity. Respondents who commuted by car were found to have the highest risk of obesity, followed by bus commuters. Those who commuted by other modes exhibited the lowest likelihood of being obese. Commuting distances below 40 km were positively associated with obesity. Beyond this threshold, the effect of commuting distance on obesity became negligible. Additionally, males were more likely to be obese than females and age had a trivial association with obesity (Appendix Fig. SM3).

Moreover, to examine the robustness of our findings, we additionally conducted an analysis by removing underweight participants. The results are shown in Supplementary Material Table SM1 and Fig. SM4-SM10. Overall, we found no substantial changes in the findings after removing underweight participants.

**Table 3**
Relative importance (RI) of predictors in explaining obesity.

| Environment variables | Commuting route | | Workplace | | Residence | | Personal variables | RI, % | Ranking |
|---|---|---|---|---|---|---|---|---|---|
| | RI, % | Ranking | RI, % | Ranking | RI, % | Ranking | | | |
| Total | 25.62 | | 23.22 | | 20.04 | | Total | 31.11 | |
| Built environment (total) | 20.67 | | 16.03 | | 15.52 | | Commuting attributes (total) | 24.49 | |
| Population density | 6.51 | 4 | 0.62 | 29 | 3.55 | 10 | Commuting mode | 12.33 | 1 |
| Restaurant density | 5.41 | 5 | 2.63 | 14 | 3.27 | 12 | Commuting distance | 10.64 | 2 |
| Intersection density | 4.04 | 8 | 1.01 | 24 | 3.56 | 9 | Commuting duration | 1.52 | 21 |
| Area of green spaces | 2.92 | 13 | 1.73 | 19 | 0.27 | 37 | Sociodemographics (total) | 6.62 | |
| Transit stop density | 0.93 | 25 | 2.33 | 16 | 4.57 | 6 | Age | 2.34 | 15 |
| Land use diversity | 0.87 | 26 | 7.71 | 3 | 0.28 | 36 | Male | 2.07 | 17 |
| Air pollutants (total) | 4.95 | | 7.19 | | 4.52 | | Household size | 1.71 | 20 |
| $O_3$ | 1.87 | 18 | 0.49 | 33 | 0.56 | 32 | Education | 0.24 | 38 |
| $PM_{2.5}$ | 1.42 | 23 | 4.15 | 7 | 0.57 | 30 | Household income | 0.17 | 39 |
| CO | 0.68 | 28 | 0.83 | 27 | 0.02 | 43 | Shanghai hukou | 0.05 | 40 |
| $NO_2$ | 0.56 | 31 | 0.29 | 35 | 3.35 | 11 | Children | 0.04 | 41 |
| $SO_2$ | 0.41 | 34 | 1.44 | 22 | 0.03 | 42 | Married | 0.01 | 44 |

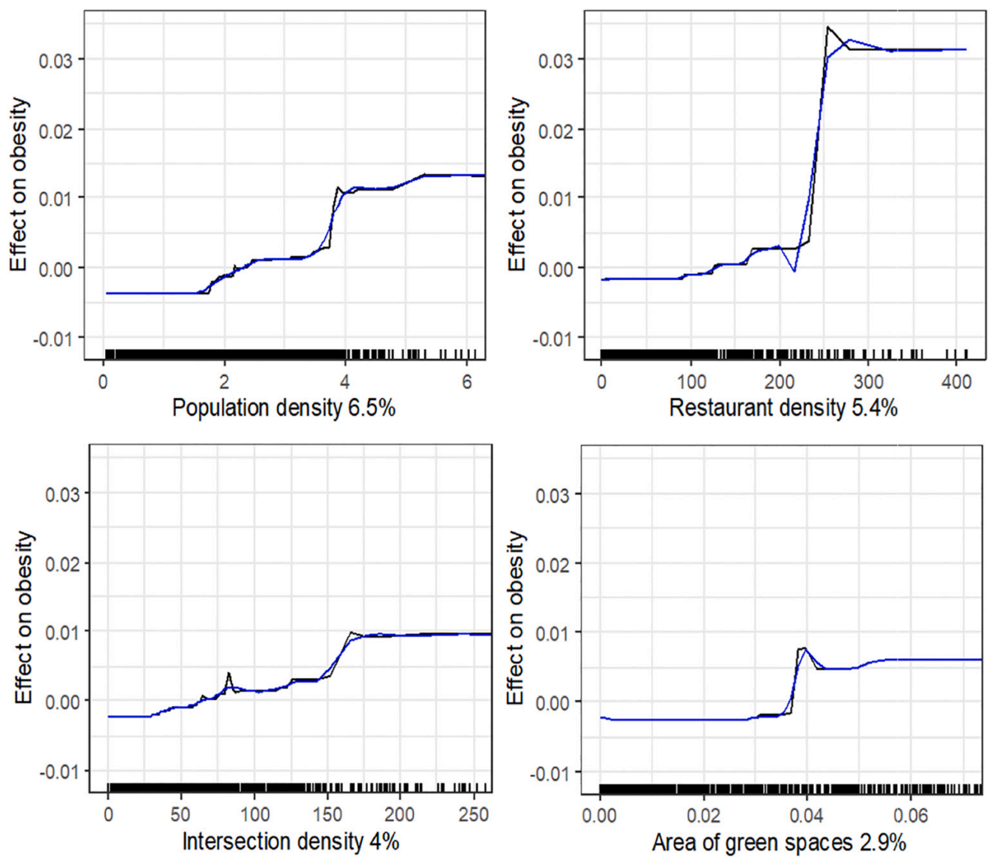


**Fig. 3.** Nonlinear relationships between key environmental variables around commuting routes and obesity.
Note: Black lines denote original curves and blue lines represent smoothed curves. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

## 4. Discussion

### *4.1. Key findings and interpretation*

This is an initial study on exploring nonlinear associations between the built environment from origins to destinations in relation to obesity. The main findings were as follows. First, the environment around commuting routes is more important than that around either workplaces or residences. Second, the environment variables had nonlinear associations with obesity and their associations differed around commuting routes, workplaces, and residences.

The environment around commuting routes was more important to predicting obesity than that around either workplaces or residences. This finding highlighted the importance of commuting routes. The commuting route serves as ties connecting residences and workplaces, which are highly related to people's outdoor environment exposure. On one hand, people may have many derived activities related to obesity during commuting, such as having breakfast and school run (Giménez-Nadal et al., 2023). On the other hand, people may spend most of their time indoor at workplaces and residences, while exposure to the outdoor environment during commuting may affect obesity through reducing sedentary behaviors. Hence, paying more attention to the environment around commuting routes is important to deepen the understanding of obesity correlates. Additionally, in line with prior research, our finding

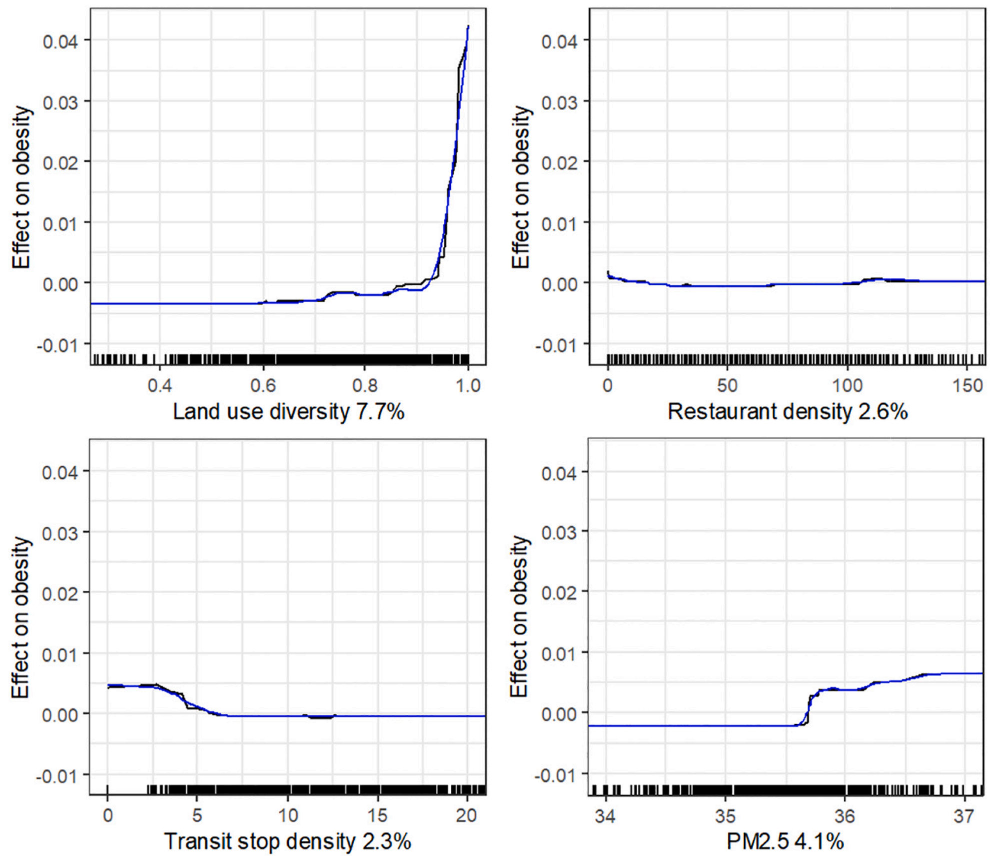


**Fig. 4.** Nonlinear relationships between key environmental variables around workplaces and obesity.
Note: Black lines denote original curves and blue lines represent smoothed curves. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

also suggested that residential and workplace built environments are important to obesity, as they are the main anchors of daily activities (e.g., food intake, exercise, and active travel) (Yin et al., 2023c). Moreover, the workplace built environment played a more important role than the residential built environment. One possible reason is that people spend most of their awake time in workplaces (Sun et al., 2024; Yin et al., 2024b).

We found the environment variables have nonlinear associations with obesity and identified three types of spatial heterogeneity in their correlations. First, several environment variables (population density, restaurant density, and intersection density) had similar associations with obesity around both residences and commuting routes, but had null association with obesity around workplaces. Population density was positively associated with obesity and the effective ranges were greater than 25,000 people/km$^2$ around residences and 17,000 people/km$^2$ around commuting routes. This finding was in line with prior research focusing on residences (Sun et al., 2022b), which suggested that higher population densities in these high-density contexts contribute to noise and congestion, reducing physical activity spaces per capita, thus increasing the risk of obesity. Restaurant density showed a positive correlation with obesity, particularly when densities ranged between 50 and 110 counts/km$^2$ around residences and between 90 and 250 counts/km$^2$ around commuting routes. A higher restaurant density provided more food choice for people, but were also easy to induce food swamp in China, resulting in an increased risk of obesity (Sun et al., 2022b). Intersection density had a positive correlation with obesity when it was below 175 counts/km$^2$ in both contexts. This finding contrasted with the literature suggesting that more interactions typically promote walkability and reduce obesity (Leonardi et al., 2017). However, our finding was supported by studies that showed more intersections are positively associated with vehicle exhaust and traffic accident (Guo et al., 2017; Huang et al., 2018), which reduced physical activity and heightened the risk of obesity.

Second, transit stop density had different associations with obesity in different spatial contexts. It showed a U-shaped relationship with obesity around residences but was negatively associated with obesity around workplaces. Consistent with previous findings, a higher density of transit stops tended to encourage more usage of public transportation, which promoted active travel and reduced car dependency, thereby lowering the risk of obesity (King & Jacobson, 2017). However, overdense transit stops might induce traffic congestion and pollution (Moore et al., 2012), which led to an increase of obesity risks. Moreover, transit stop density around commuting routes had a trivial association with obesity. This made sense because most of respondents did not have a mode transfer in Shanghai (Chen et al., 2024).

Third, several environmental variables were only associated with obesity in a specific context. Around residences, the concentration of $NO_2$ was positively associated with obesity. Previous evidence suggested that high levels of $NO_2$ in ambient air were related to the increased risks of overweight and obesity, particularly among vulnerable populations (de Bont et al., 2021). For one thing, air pollution contributed to chronic diseases like asthma, heart disease, and lung cancer, which could affect body weight (Dong et al., 2014; Kim et al., 2016). For another, air pollution triggers oxidative stress and inflammation in adipose tissue, linking them to obesity and metabolic syndrome (Li et al., 2015; Ponticiello et al., 2015), while also promoting sedentary behavior by disrupting regular exercise (Hautekiet et al., 2022; Yu et al., 2017). Around commuting routes, the area of green spaces had a slightly positive linkage with obesity. This was inconsistent with the literature, which highlighted that people tended to conduct more physical activity when

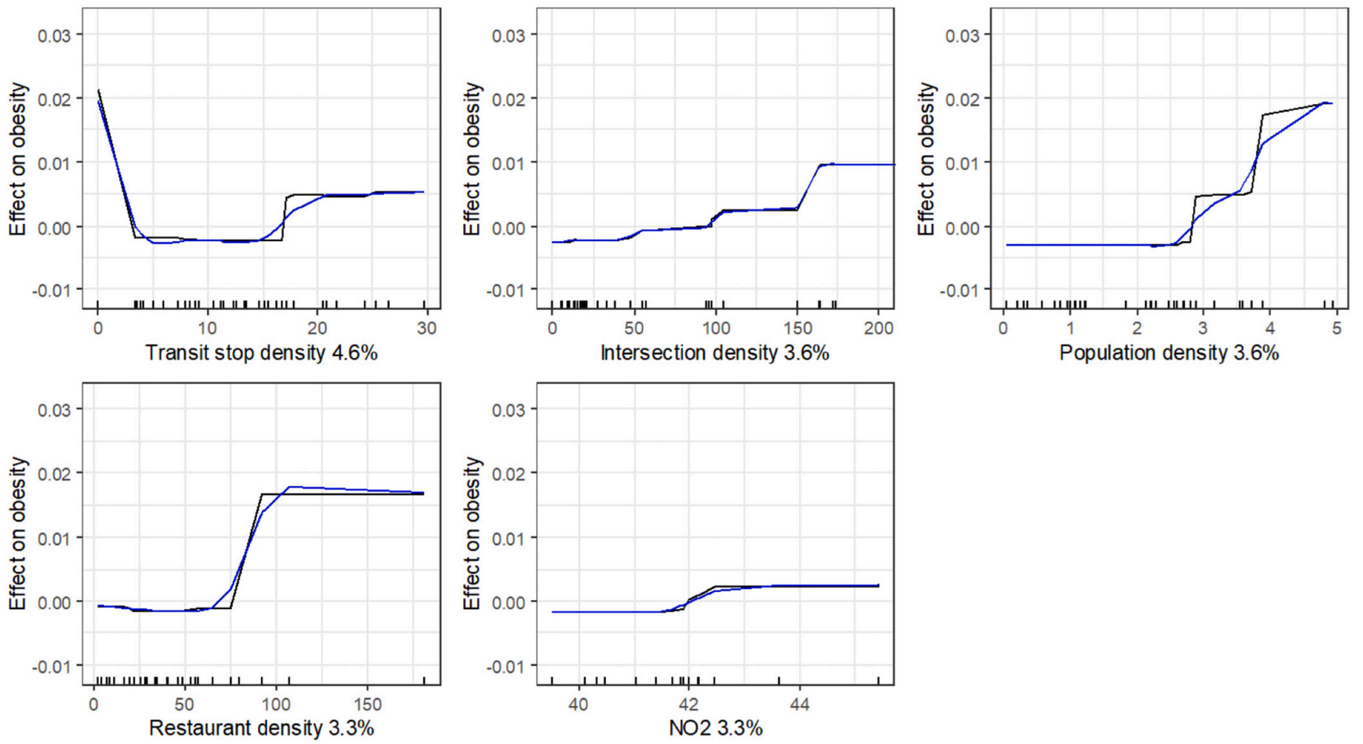


**Fig. 5.** Nonlinear relationships between key environmental variables around residences and obesity.
Note: Black lines denote original curves and blue lines represent smoothed curves. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

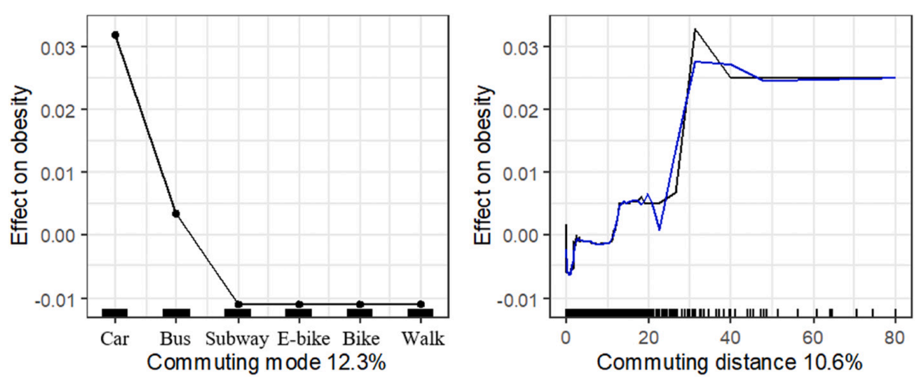


**Fig. 6.** Nonlinear relationships between key commuting variables around commuting routes and obesity.
Note: Black lines denote original curves and blue lines represent smoothed curves. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the area of green space increased (Chen et al., 2022; Liu et al., 2021b), resulting in reduced risks of being obese (Luo et al., 2020). However, more green spaces on commuting routes often induced detouring, which prolonged commuting distances and durations, leading to a worse commuting experience and reduced leisure time for physical activity (Chen et al., 2024), which plays an essential role in affecting obesity (Burgoine et al., 2015). Around workplaces, land use diversity and $PM_{2.5}$ had positive relations with obesity. Workplace neighborhoods with mixed land use exceeding 0.9 had a higher level of noise and more crowding, which might induce obesity. Moreover, overly-mixed land use induced many facilities that could increase health risks, such as clubs (Yin et al., 2024a). However, when mixed land use was below 0.9, it had limited association with obesity, which suggested that the interventions in land use diversity might not achieve the goal of reducing obesity. Moreover, higher levels of $PM_{2.5}$ around workplaces might be related to industrial activities or high traffic flow at these locations, which could restrict outdoor activities, thereby increasing health risks (Sun et al., 2023).

Moreover, commuting attributes made substantial contributions to obesity risks. Car commuting was linked to increased sedentary behavior and obesity (Ding et al., 2014; Wang et al., 2019; Wang et al., 2020) while bus commuters faced delays and crowdedness that could limit physical activity, raising BMI (Christian, 2012). Conversely, subway commuters experience lower BMI, benefiting from the subway's efficiency and the physical activity involved in reaching and leaving stations (Bassett et al., 2008; Morency et al., 2011). Commuting distance below 40 km was positively correlated with obesity. This was consistent in the literature, which found that longer commuting distances were associated with non-active travel and longer commuting durations, resulting in less physical activity and higher risks of being obese (Raza et al., 2021).

### 4.2. Policy implications

This study provides valuable insights that can inform policy recommendations and interventions aimed at reducing obesity and shaping healthy cities. First, policymakers should expand their focus beyond residential area planning to include individuals' environmental exposure throughout the whole commuting process across origins, routes, and detentions. Given the importance of environments around residences, workplaces, and commuting routes, with commuting routes having the greatest impact on obesity, policymakers should pay more attention to improving the commuting environment. Therefore, health-oriented land use policies should be tailored to the various spatial locations of individuals' daily activities.

Second, policymakers should consider adopting various strategies of spatial optimization as the built environment impacts on obesity have spatial heterogeneity, which needs to be mindful of the thresholds of these built environment elements. Higher population density, restaurant density, and intersection density around residences and commuting routes, and excessive land use diversity around workplaces are unfavorable to healthy weights. Hence, de-densification spatial strategies should be considered in Shanghai. Moderate transit stop density can reduce obesity around workplaces and residences, indicating that transit-oriented development can achieve additional health benefits.

### 4.3. Strengths and limitations

This study has some strengths compared to previous studies. First, it develops a comprehensive framework linking the built environment and obesity from a commuting perspective. By considering the built environment around residences, routes, and workplaces in one model, it shows that the built environment around commuting routes is more important than that around residences and workplaces. Second, it highlights the variability in the nexus between the built environment and obesity across different spatial contexts, which helps planners to design the built environment specifically. Third, it relaxes the linear assumption in the literature. By considering the nonlinear effects based on the machine learning approach, this study provides new findings on thresholds of built environments on obesity.

However, we acknowledge several limitations in the present study. First, the cross-sectional design prevented the inference of causal relationships between predictors and obesity. Future studies should focus on acquiring longitudinal data and leverage advanced models to better assess the causal relationship. Second, we mainly used the shortest distances between residences and workplaces to measure commuting routes, as most respondents reported they followed the shortest routes to commute. However, this may be subject to recalled biases and travel purposes (i.e., school run). Future studies can use global positioning system devices to collect the real commuting routes and validate our findings. Third, the relative importance and thresholds identified in this study may not generalize to other contexts. Additional empirical studies are needed to validate the identified thresholds.

## 5. Conclusion

Our study demonstrated that the commuting environment, particularly around commuting routes, contributed more to obesity than that around residences or workplaces. Moreover, the built environment's impact on obesity exhibited spatial heterogeneity and nonlinearity. Within certain thresholds, population density, restaurant density, and intersection density were positively related to obesity around both residences and commuting routes, but were not associated with obesity around workplaces. Transit stop density had a U-shaped correlation with obesity around residences, while it had a negative association with obesity around workplaces. Several environmental variables were only associated with obesity in a specific context. These findings emphasize the importance of considering the commuting environment within a comprehensive framework that includes residences, routes, and workplaces. Additionally, recognizing the nonlinear relationships and spatial heterogeneity of environmental factors can inform more nuanced healthy city planning and public health strategies aimed at reducing obesity.

## CRediT authorship contribution statement

**Chun Yin:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Zhe Zhang:** Writing – review & editing, Visualization, Software. **Shaoqing Dai:** Software, Data curation. **Yiyi Chen:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

## Declaration of competing interest

None.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2025.105842.

## Data availability

Data will be made available on request.

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