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Effects of built environment factors on obesity risk across three types of residential community in Beijing

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ABSTRACT

Introduction: There is strong evidence in Western cities that neighborhood-level characteristics of the built environment are linked with a higher risk of overweight or obesity among residents. Due to the rapid urbanization during the last several decades, many types of residential community have formed and coexisted in the major cities of China. These communities provide residents with different built-environment features and lifestyles. However, it remains unclear whether the community type affects the risk of overweight and obesity among residents.
Methods: The present study investigated the associations of built-environment characteristics and the bodyweight status (normal vs. overweight or obese) of 4,440 residents from three main types of community (i.e., commercial, work-unit, and traditional communities) in Shijingshan district, Beijing. Multilevel logistic regression and the random forest approach were adopted to investigate both the significance and relative importance of neighborhood-level factors of the built environment.
Results: The results of multilevel logistic regression suggest that the community type has a significant association with the obesity risk. In addition, the land-use mix, the number of water features, the number of supermarkets and groceries, street intersections, and the normalized difference vegetation index are negatively related to the odds of obesity. The number of transit stops is positively associated with the odds of obesity. Random forest analysis reveals significant disparities in the relative importance of population structure and the built environment factors among the three types of community. Furthermore, we find a notable difference between the results of the multilevel logistic model and random forest model. Hence, both the significance and relative importance of neighborhood-level factors of the built environment should be considered.
Conclusions: The findings indicate that the community type has a significant association with the risk of overweight. Tailored policies and urban renewal interventions should be developed for different community types.

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1. Introduction

A person who is overweight or obese has an excessive level of body fat, which is associated with increasing incidence rates of chronic diseases and conditions, such as diabetes, stroke, and cardiovascular disease (Piché et al., 2018). As a global health problem, more than one-third of adults worldwide are overweight and more than 650 million are obese as of 2016 (World Health Organization, 2020). China has experienced intensive urbanization for the past several decades, which has led to rapid changes in the built environment, lifestyles, and dietary habits of Chinese people (Wu et al., 2017). With its increasing incidence of obesity, China has had the world's largest obese population since 2017 (Wang, Wang and Qu, 2017). It has been shown that the incidence of overweight or obesity among Chinese adults will reach 65.3% by 2030 (Pan et al., 2021). There is thus an urgent need to tackle the prevalence of overweight and obesity in China.

Researchers in many disciplines and fields, namely public health, clinical medicine, and urban planning, are exploring how to control the prevalence of overweight and obesity. The body mass index (BMI) is an effective and simple index with which to estimate the degree of an individual's obesity at the population level, though it is too rough to gauge the degree of body fat distribution (Yu et al., 2015). In the field of urban planning, there is strong evidence that the urban built environment affects the bodyweight of urban residents (Garfinkel-Castro et al., 2017; Huang, Moudon, Cook and Drewnowski, 2015). There are three major mechanisms driving the effect, namely the promotion of active transportation, such as walking and cycling (Brown, Moodie, Cobiac, Mantilla and Carter, 2017a); an increase in recreational physical activity (Kim et al., 2017); and the provision of a healthy food environment (Cobb et al., 2015).

Although many empirical studies have investigated the effect of the built environment on bodyweight outcomes, there are several research gaps to be addressed. First, most evidence of the associations between built-environment factors and the risk of being overweight or obese comes from the low- or medium-density context of cities in Western countries (Li, Harmer, Cardinal, Bosworth and Johnson-Shelton, 2009). There is little evidence available about whether such associations exist for the high-density urban context of China. There is appreciable variation in the population density, transportation mode choice, and urban development pattern between major cities in China and those in Western countries. Second, and more specifically, three major residential community types (i.e., traditional community, work-unit community, and commercial community) have coexisted in major Chinese cities during rapid urbanization occurring over the past decades (Guan et al., 2020). Accompanied by the changing demands of residents in different time periods, the development of these community types reflects varying lifestyles and built environment characteristics (Lei and Lin, 2021). As an example, most traditional communities are in old urban areas with mixed land use and high destination accessibility but with less open space or greenery. Commercial communities are characterized by a facility-rich built environment but are sometimes located in remote areas. Work-unit communities are often in close proximity to workspaces, and the residents generally have a shorter commuting distance relative to those in other community types (Guan et al., 2020). However, to our knowledge, there has been little research on the association between the community type and the risk of overweight and obesity. Third, there is evidence of a relationship between the built environment characteristics and the risk of overweight and obesity, but the relative importance of the effect of each influencing factor on the risk of overweight and obesity remains unclear.

To address the abovementioned gaps in the literature, this study explores the relationship between the community type and the risk of being overweight or obese for 4440 individuals living in three types of community in Beijing, China using multilevel logistic regression models. It further examines the relative importance of population structure and the built environment characteristics to the obesity risk in the three types of community using random forest models. The study is expected to enrich the literature on the relationship between the built environment and obesity in high-density urban contexts in China and shed light on obesogenic environments to the benefit of government officials and urban planners.

2. Literature review

2.1. The built environment and the risk of being overweight or obese

The prevalence of people being overweight or obese is a global health concern that has multiple factors at national, community, and individual levels (Ghosh and Bouchard, 2017). Among these factors, characteristics of the neighborhood built environment are important to efforts of increasing or reducing the risk of being overweight or obesity (Sallis et al., 2009). Information on these characteristics is available across different genders (Huang et al., 2015), age groups (Berke et al., 2007), and races (Wen and Kowaleski-Jones, 2012).

There are three major mechanisms underlying the effect of built environment characteristics on the risk of being overweight or obese; i.e., the urban built environment facilitates or constrains the healthy eating habits of residents, the adequacy of recreational physical activity, and the regularity of active transportation (Brown et al., 2017a,b; Cobb et al., 2015).

In terms of healthy eating habits, studies note that a high level of exposure to a neighborhood supermarket can reduce adiposity (Caspi et al., 2012; Jia, Xue, Cheng and Wang, 2019). A higher density of groceries can encourage community residents to have a balanced diet through the greater intake of vegetables and dietary fiber (Caspi et al., 2012). Conversely, studies find positive associations between the distribution of fast-food restaurants and an individual's BMI (Li et al., 2009; Wu et al., 2017). High accessibility to fast-food restaurants may increase the risk of obesity because of the excess calorie intake and low diet quality associated with these restaurants (Rahmanian and Gasevic, 2014).

In terms of adequate recreational physical activity, studies reveal the positive effect of recreational physical activity on obesity prevention and treatment (Cerin et al., 2013; Mackenbach et al., 2014). Adults, and especially old people, can maintain a healthy body weight status by adequately participating in recreational physical activities and by reducing their levels of sedentary behavior (Kim et al., 2017). A systematic review shows that characteristics of a built environment such as accessible greenery, recreational facilities, and a pleasant streetscape are positively associated with increased recreational physical activity and lower obesity risk (Barnett et al., 2017).

In terms of regular active transportation (e.g., walking and cycling for transportation purposes), an international study finds that the active transportation level has a negative association with a country's obesity rate (Bassett et al., 2008). Many studies explore the characteristics of a walking/cycling-friendly built environment (Brown et al., 2017a,b; Guan et al., 2020; Jiang et al., 2021). According to a systematic review, separated sidewalks or cycling routes, a short commuting distance, proximity to greenery, and a high population density are the main factors of a built environment associated with a high level of active transport behavior (Fraser and Lock, 2011). Aside from this, residents tend to choose an active transportation mode and maintain a healthy BMI when there are convenient public transportation and accessible destinations (van Soest et al., 2020).

2.2. Community type and resident lifestyles in China

Community planning and design in the Western context has undergone a conceptual transformation from car-oriented theory to human-oriented theory (Ellis, 2002). To solve urban issues caused by increased automobile dependence, such as urban sprawl, traffic congestion, and the prevalence of chronic disease, theories such as new urbanism and smart growth promote active lifestyles by creating a walking-friendly and transit-friendly environment (Calthorpe, 1993; Duany, 2010). To date, Western research mainly uses the neighborhood density and location (i.e., urban and suburban) as criteria for community delineation (Handy et al., 2005).

Empirical evidence in the Western context often emphasizes the effects of the 5D factors of the built environment (i.e., density, design, destination accessibility, distance to transit, and diversity) on a resident's risk of overweight and obesity (Sallis et al., 2009). However, huge differences between the Chinese and Western contexts, such as differences in the resident's living habits, urban density, and dominant travel mode, may mean that the effects of these characteristics of the built environment differ widely in China (Pan et al., 2021; Wang, Shao, Yin and Guan, 2021).

Furthermore, the different types of community that have formed during past decades in Chinese cities may have different effects on the resident's bodyweight status. To date, there are three major community types in major Chinese cities according to the type of housing, namely traditional, work-unit, and commercial communities (Wang, Song and Xu, 2011).

The work-unit community (called *Danwei* in Chinese) is a distinctive community type in China. State-owned enterprises often built work-unit communities and provided residence units to employees for free or at a low price as a social benefit from the 1950s–1980s (Lei and Lin, 2021). These communities have been transformed from collective-owned to personal-owned after the housing reforms of China. Work-unit community residents can easily access workspaces and other living facilities (e.g., kindergartens, hospitals, places of recreation, and supermarkets) within a short walking distance. Hence, the work-unit community is a spatial agglomeration with mixed living and working functions (Li, Zhu and Li, 2012).

Traditional communities mainly comprise low-rise residential buildings built since the 1950s (Gao et al., 2016). Traditional communities are characterized by poor physical environments, a lack of green/open spaces, and inner-city locations. The number of existing traditional communities remains considerable, although some traditional communities were recently demolished in the process of urban renewal (Lei and Lin, 2021).

Since the housing reforms of China in the 1990s, work-unit housing has no longer been offered by state-owned enterprises (Yang, Shen, Shen and He, 2012). Residents instead purchase a commercial residence according to their preferences and economic situation. As a later-appearing community type, commercial communities (i.e., communities with commercial residences) are mostly gated communities with admirable green spaces and recreational facilities within the community (Lei and Lin, 2021). Additionally, owing to the popularity of private cars in China since the 1990s and the ample parking facilities at commercial residences, automobiles have become one of the main transportation modes for commercial community residents (Guan et al., 2020).

Different types of community have unique built environments, economic status, and human relations (Y. Zhao and Chai, 2013). As an example, there is evidence that residents in a work-unit community have shorter commuting trips, lower travel frequencies, and less reliance on private cars compared with those in a commercial community (Zhao and Chai, 2013). A national longitudinal study on the self-rated health conditions of residents belonging to different community types reveals that the self-rated health points of people older than 50 years of age are sensitive to the community type, whereas there is no difference in the younger adult group (18–50 years of age) (Lei and Lin, 2021). Another study classifies 20 communities in Xi'an into four types according to the community density level and building age and finds that diversity, aesthetic elements, and safety are positively associated with the mental and physical health of residents in new communities (Gao et al., 2016).

2.3. Analysis of the relationship between obesity and the built environment

Many empirical studies explore the associations between obesity and characteristics of the built environment (Berke et al., 2007; Garfinkel-Castro et al., 2017; Li et al., 2009). According to the data type and research methodology, these studies can be classified into cross-sectional studies (Wang et al., 2021; Yang et al., 2018) and causal-inference supporting studies (V. Brown et al., 2017). Despite there being different requirements of the data types used in cross-sectional and causal-inference supporting studies, these studies adopt similar statistical methods, such as the use of logistical regression (Jia and Fu, 2014), multivariate regression (An and Zheng, 2014), multilevel regression (Hinojosa et al., 2018), and generalized linear models (Wong et al., 2016). These statistical methods are widely applied in analyzing the relationships between obesity and characteristics of the built environment. However, the abovementioned methods mainly focus on investigating the statistically significant associations between the outcome and independent variables (Cheng et al., 2020) and fall short in evaluating the relative importance of significant independent variables.

With the rapid advance of artificial intelligence, new machine-learning data-analysis methods have emerged. Some studies use support-vector machines (Cesare et al., 2019), fuzzy logic (Giabbanelli et al., 2014), and the gradient boosting decision tree model (Wang et al., 2021) to investigate the obesity–environment relation. These machine learning methods are used in different scenarios to solve specific problems and improve the accuracy and robustness of the data analysis.

The random forest, as an ensemble learning method (Breiman, 2001), is gradually being introduced to public health and medical research for its ability to detect nonlinear relationships and the relative importance of input features (Schultz et al., 2020). Previous studies detect the effects of the characteristics of the built environment on the travel mode choice (Kim, Kwon and Horner, 2021), variation in the concentration of particles with a diameter of less than 2.5 μm (Chen et al., 2021), and respiratory health (Xu, Zhao and Wang, 2018). A cross-sectional study discovers the nonlinear relationship and threshold effects of the walking time of older adults and the built environment using the random forest (Cheng et al., 2020). The population density, park accessibility, and street connectivity are the most important characteristics for increasing the walking time among old people (Cheng et al., 2020). Although studies using the random forest are becoming popular in the field of public health, there remains little application of this method in obesity–environment research. To the best of our knowledge, only one such published study uses the random forest to investigate the relationship between school and neighborhood environments and adiposity among teenagers in California, United States (Hinojosa et al., 2018). The study shows that the most important environmental factors are the distance to a highway and violent crime, because of the potential effect of perceived safety on the physical activity level of teenagers (Hinojosa et al., 2018).

In summary, there is strong evidence of an association between the neighborhood-level built environment and the risk of overweight and obesity. However, relevant studies are often conducted in Western cities and may not directly relate to China. In particular, these studies neglect the effect of the community type, which is a critical and unique built environment feature in China, on a resident's risk of overweight and obesity. To the best of our knowledge, only a few studies investigate the effects of the community type on the overall active transportation and health levels in China (Guan et al., 2020; Lei and Lin, 2021), and none of these studies investigates the effects on the risk of overweight and obesity obese. It is therefore important to explore the association between the community type and an individual's risk of overweight and obesity and to detect the relative importance of built environment factors. Furthermore, we explore whether the effects of the neighborhood-level factors of the built environment vary across community types. The results of this study can enrich the policymaker's understanding of obesogenic environments and provide fine-grained evidence for planning interventions.

3. Method

3.1. Study area

Beijing, the capital of China, is situated in Northern China (Beijing Municipal Commission of Planning and Natural Resources, 2018). Beijing has 16 districts with a total population of 21.89 million people as of 2021 (National Bureau of Statistics of China, 2021). In this study, 45 communities in Shijingshan district in western Beijing were selected as the study area (Fig. 1). The prevalence of obesity (26.9%) in Shijingshan, an economically developed area, is higher than the national average (16.4%) (Beijing Municipal Health Commission, 2018).

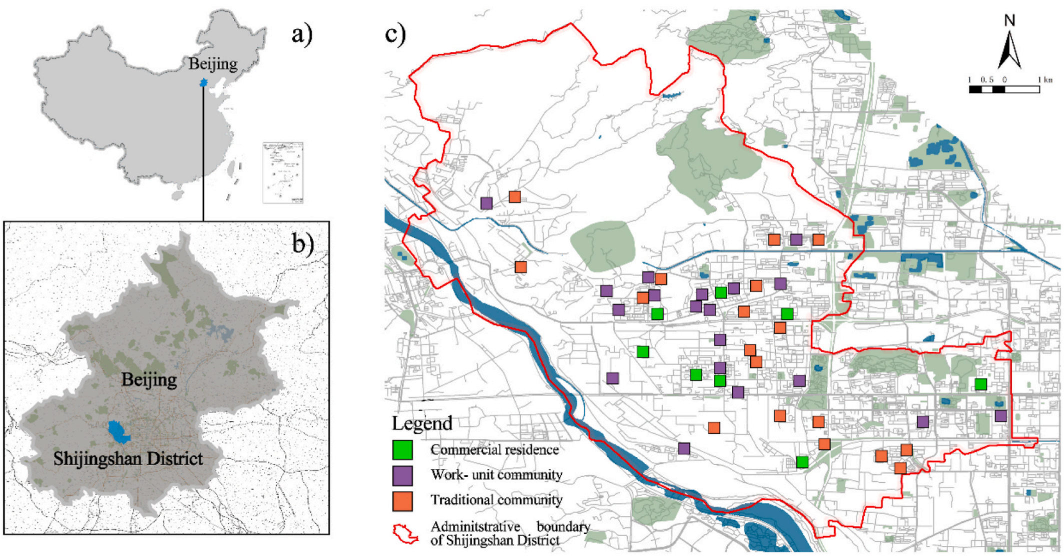

Fig. 1. a) Location of Beijing in China. b) Shijingshan district in Beijing. **c)** Locations of 45 selected communities in Shijingshan district.

Table 1
Characteristics of three types of community in Shijingshan, Beijing.

Community type	Neighborhood name	Age	Gatedness	Housing acquisition mode	Job-housing relationship	Commercial density class*	Community management level (property management fee)(yuan/m^2)
Commercial community	Zhonghai king palace … Shijijiayuan	Late 1990s - Mid 2010s	Gated	Private purchase	High commuting distance (Compared to work-unit community)	Level 1 & 2	2.3–10
Work-unit community	Subway group Community … Beijing heavy industry Community	Early 1980s – Mid 1990s	Gated	Housing reform & work-unit distribution	Job-housing balance	Level 2 & 3	0.62–1.56
Traditional community	Gucheng road Community … Shiwangping Community	Late 1950s – Early 1990s	Mix (Non-gated & gated)	Housing resettle & inheritance	High commuting distance (Compared to work-unit community)	Level 3 & 4	0–0.6

Notes: Commercial density class: Level 1, $<$10 commercial facilities/km^2; Level 2, 10–100 commercial facilities/km^2; Level 3, 100–200 commercial facilities/km^2; Level 4, $>$200 commercial facilities/km^2; ** Distance estimated in Baidu Map (http://map.baidu.com).

The bodyweight and height information were retrospectively retrieved from neighborhood-level health examinations of Shijingshan district conducted by a major tertiary hospital in April 2018. The neighborhood-level health examinations followed a two-step cluster random sampling strategy. Five communities were randomly selected in each of the nine administrative sub-districts of Shijingshan district. Well-trained healthcare workers from the hospital entered these communities and randomly selected 70–120 voluntary adult residents in each community for physical examination. Three exclusion criteria were applied to the potential respondents, i.e., residents having lived in the current community for less than 5 years, residents younger than 18 years of age, and pregnant women. The collected data via the survey included the respondent's health status and individual information, including his or her home address, height, weight, age, and gender. For privacy and confidentiality reasons, all personal data were made anonymous. In total, the survey recruited 4941 adult respondents, around 1% of the total adult population in Shijingshan district (Beijing Municipal Commission of Planning and Natural Resources, 2018).

All addresses of the respondents were geocoded using ArcGIS Desktop 10.5 (ESRI Inc., USA). A total of 4,440 records from 45 communities were successfully geocoded, with a matching ratio of 89.9% to the community address. Based on the statistics of neighborhood characteristics (e.g., age, gatedness, housing acquisition mode, job-housing relationship) collected by local government in Beijing (Beijing Municipal Commission of Planning and Natural Resources, 2018), these 45 communities were classified into three representative types, i.e., traditional community, work-unit community, and commercial community (Table 1). The present study was approved by the ethics committee of Tianjin University.

3.2. Data and variables

This study used the bodyweight status (overweight or obese vs. normal) as the outcome variable. As a measurement of central obesity, body mass index (BMI) was calculated following the formula BMI = weight (kg)/height (m)^2. A BMI $\geq$ 24 was considered overweight, whereas a BMI $\geq$ 28 was considered obese following the Chinese guidelines for adults (Zhou, 2002). All participants were divided into the overweight or obese group (BMI $\geq$24) and normal group (BMI <24). Among the 4440 respondents, the average BMI was 22.88, and 32.27% of the respondents were in the overweight or obese group.

Independent variables assumed to have associations with the risk of overweight or obesity were categorized into the individual level (level 1) and neighborhood level (level 2) (Appendix A). Sociodemographic data (age and gender) were considered as independent variables of the individual level.

The independent variables at the neighborhood level were collected for a 800-m street network buffer zone around the centroid of each respondent's residential address (Fig. 2), following previous research (P. Jia et al., 2019). Thirteen characteristics of the built environment at the neighborhood level were considered on the basis of the 5D framework (i.e., density, design, destination accessibility, distance to public transit, and diversity), as listed in Appendix A (Ewing and Cervero, 2010). Additionally, the overall greenery and community type were considered as neighborhood-level variables. The normalized difference vegetation index (NDVI) was used as a measure of a neighborhood's general greenery and calculated using Sentinel-2 imagery (Drusch et al., 2012). NDVI values range from 0 to 1. The community type (i.e., the commercial community (reference category), work-unit community, or traditional community) was recorded as a categorical variable.

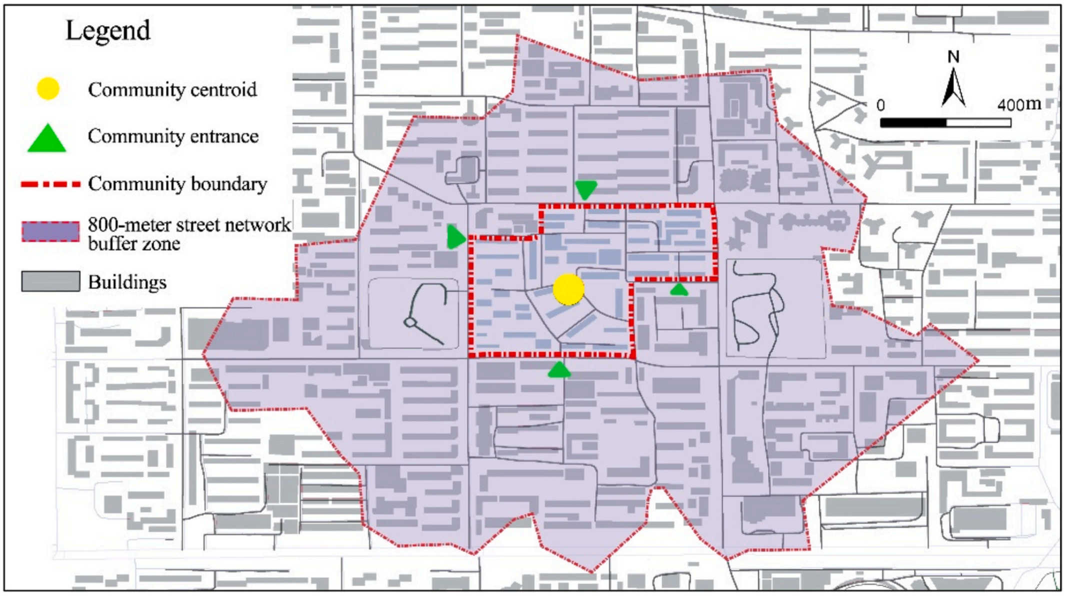

Fig. 2. Schematic of an 800-m street network buffer zone around the centroid of a respondent's residential address.

3.3. Statistical analysis

In step 1 of the statistical analysis, multicollinearity among the independent variables, except for the community type, was tested using the variance inflation factor (VIF). Two variables with a VIF ≥4, namely the restaurant POI and public service POI, were removed from subsequent analysis. In step 2, a multilevel logistic regression model with random intercepts and fixed slopes was used to evaluate the associations between an individual's body weight status and the built-environment factors. Individual respondents (level 1) were clustered within the 45 selected communities (level 2) in Shijingshan district. The odds ratio, P-value, and 95% confidence interval of each predictor variable are reported.

There were two objectives to step 2. First, we could explore whether the community type is associated with an individual's risk of being overweight or obese. Second, we could find other significant predictors of an individual's risk of overweight and obesity.

In step 3, we further analyzed the relative importance of population structure (i.e., age and gender) and built-environment factors using the random forest approach. The relative importance of the variables represented the relative enhancement when the model prediction error was reduced. There are two main methods of estimating the relative importance for the random forest model, namely the mean square error and the mean decrease in the Gini coefficient (Breiman, 2001). A previous study suggests that using the mean square error is a more reliable method of estimating the relative importance of a variable (Genuer et al., 2010), and we thus used the mean square error in steps 3 and 4.

The initial results of steps 2 and 3 show that the community type is associated with the outcome and its relative importance is high. Hence, in step 4, we split the data by community type. Three random forest models were built to further explore the relative importance between population structure (i.e., age and gender) and built environment factors in each of community type.

In step 4, we described relative importance at two levels, i.e., overall level and built environment level. At overall level, we considered all built environment factors as one factor to explore the relative importance of built environment and population structure factors (i.e., age and gender) in each community type. At built environment level, we further explore the relative importance of each built environment factor in each community type.

Random forests or random decision forests are an ensemble learning method for regression in which multiple decision trees are constructed (Breiman, 2001) (Fig. 3). Simultaneously, each decision tree is built to guarantee low bias and optimal classification performance (Calderoni et al., 2015). We randomly selected certain numbers (m_{try}) of the prediction variables for splitting at each node of the tree; m_{try} is usually taken as the square root of the total number of prediction variables. Generally, a greater number of decision trees results in higher accuracy and greater robustness of the model. Additionally, an important feature of the random forest model is the out-of-bag (OOB) error, which can be used to estimate the performance of the random forest model. In this study, the OOB error of the model became steady when there were approximately 4,000 trees. We therefore selected $n_{tree} = 4,000$ and $m_{try} = 3$ after testing the classification performance (n_{tree} range from 500 to 4,000) in this study.

The descriptive statistics of the outcome and independent variables (e.g., minimum, maximum, mean, median, and standard deviation (SD)) are reported. The multilevel logistic model and random forest model were respectively processed using the bruceR package (Bao, 2020) and randomForest package (Liaw and Wiener, 2002) (R version 4.1.0).

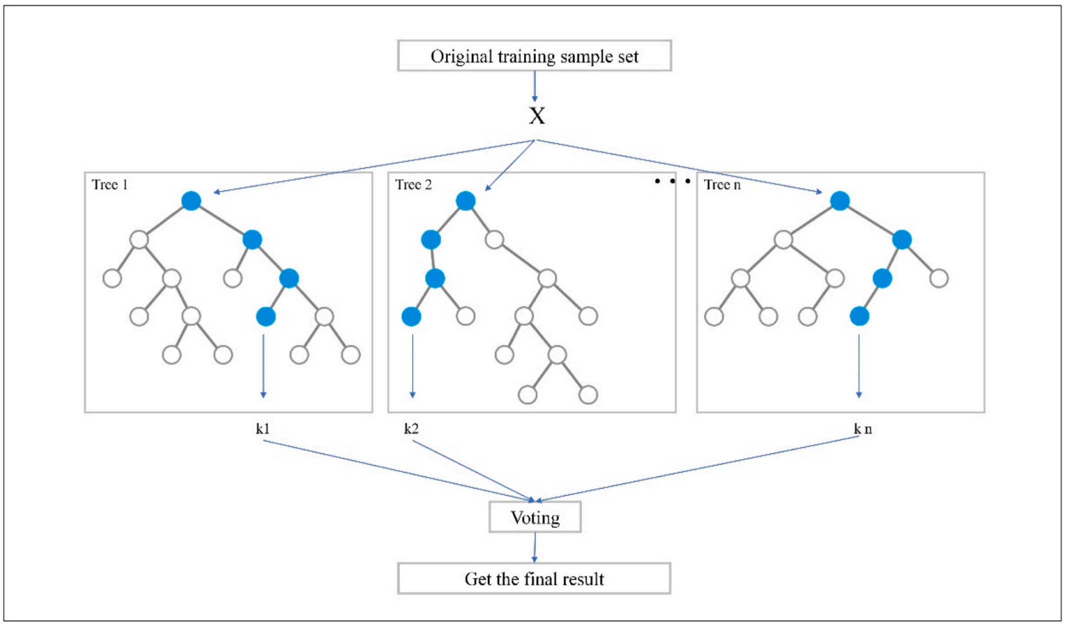

Fig. 3. Illustration of the random forest approach.

4. Results

4.1. Descriptive statistics

Table 2 presents the descriptive statistics for all respondents. Overall, the mean BMI of all respondents is 22.88 kg/m^2, with around one-third (32.3%) of the respondents being overweight or obese. There are fewer male respondents than female respondents (45.4% vs. 54.6%), and the ratio of the overweight or obese group is slightly higher among female respondents than male respondents (33.2% vs. 31.2%). The numbers of participants living in a commercial community, work-unit community, and traditional community are 1,773, 1,268, and 1,399, respectively. The proportion of overweight or obese respondents in the traditional community is higher than the proportions in the work-unit community and commercial community (53.5% vs. 30.9% vs. 16.5%).

The descriptive statistics of neighborhood-level variables of the built environment are given in Table 3. The traditional community has the highest population density (14,466.47 people/km^2), land-use mix degree (0.80), park POI (0.84), and street intersection (13.35) among the three community types and the lowest water feature POI (0), transit stop (20.17), street curvature (1.05), and NDVI (0.17). The commercial community has the highest supermarket and grocery POI (4.23), workplace POI (49.25), transit stop (40.63), and NDVI (0.28). The work-unit community has the lowest land-use mix degree (0.44), supermarket and grocery POI (2.99), and street intersections (11.31).

4.2. Results of multilevel logistic regression

Table 4 presents the results obtained using the multilevel logistic model. In the case of Model 1, all built-environment variables, including the community type, were entered into the model. In the case of Model 2, individual variables, including the age and gender, were additionally added into the model. The results obtained using Model 2 show that the transit stop is positively associated with the probability of obesity. In contrast, the land-use mix, water feature POI, supermarket and grocery POI, street intersections, and NDVI are negatively related to the odds of obesity. More importantly, the probability of obesity differs between the respondents in the three types of community. Compared with those living in commercial communities, residents living in work-unit communities are 4.8% more likely to be overweight or obese (OR = 1.048, CI = 1.015–1.081) and residents living in traditional communities are 42% more likely (OR = 1.423, CI = 1.357–1.490).

In terms of individual characteristics, the female respondents are slightly more prone to being overweight or obese compared with the male respondents (OR = 1.010, CI = 1.008–1.012). There is a significant positive association between the respondent's age and the possibility of being overweight or obese, which was in line with previous findings (Berke et al., 2007; Wang et al., 2021).

4.3. Relative importance of significantly associated explanatory variables

We first used the random forest model to detect the relationships among all explanatory variables (including the community type) and a resident's body weight status in the 45 communities (Fig. 4). The results show that the relative importance of the community type ranks first (19.61%) among all the explanatory variables. This result indicates that community type has a crucial effect on a resident's obesity risk, which is in line with the results obtained in step 2 (Section 4.2).

Hence, we further split the data by community type to examine the variations between all explanatory variables and body weight at overall level and built environment level among the three types of neighborhoods. Only the significant explanatory variables obtained in Step 2 were used, namely respondent's age and gender, the land-use mix, water feature POI, supermarket and grocery POI, transit stop, street curvature, street intersection, and NDVI.

The results of the relative importance of explanatory variables for the three types of neighborhoods are given in Table 5 and Table 6. At overall level, there are notable differences among the three types of community (Table 5). The relative importance of built environment in work-unit community (58.25%) is higher than that in other two community types (Fig. 6). The relative importance of respondent's age in traditional community (47.78%), is higher than that in other two community types (Fig. 7).

Table 2
Statistics for all respondents in Shijingshan, Beijing, sampled in 2019 (N = 4,440).

	Overweight or obese	Normal	Total
Respondent characteristics	1,433 (32.3%)	3077 (67.7%)	4440 (100%)
Age (n, %)			
18–60 years	990 (31.9%)	2112 (68.1%)	3102 (69.9%)
≥60 years	443 (33.1%)	895 (66.9%)	1338 (30.1%)
Gender (n, %)			
Male	628 (31.2%)	1386 (68.8%)	2014 (45.4%)
Female	805 (33.2%)	1621 (66.8%)	2426 (54.6%)
Community type (n, %)			
Commercial community	292 (16.5%)	1481 (83.5%)	1773 (39.9%)
Work-unit community	392 (30.9%)	876 (69.1%)	1268 (28.6%)
Traditional community	749 (53.5%)	650 (46.5%)	1399 (31.5%)
BMI, kg/m^2 (mean ± SD)	25.83 ± 2.30	21.52 ± 1.86	22.88 ± 2.82

Note: BMI = body mass index; Overweight or obese: BMI ≥24; Normal: BMI <24; SD = standard deviation.

Table 3
Statistics for neighborhood-level variables of the built environment in Shijingshan, Beijing, sampled in 2019 (N = 4,440).

Variable	Full dataset	Community type		
		Commercial community	Work-unit community	Traditional community
Built environment characteristics: mean (standard deviation)				
Population density ($N/\ km^2$)	12,039.6 (5,356.92)	10,872.82 (5,585.96)	13,359.13 (5,068.89)	14,466.47 (3,141.93)
Land-use mix (≥ 0)	0.59 (0.30)	0.52 (0.29)	0.44 (0.28)	0.80 (0.21)
Water feature POI (N)	0.04 (0.27)	0.11 (0.41)	0.02 (0.17)	0 (0)
Supermarket and grocery POI (N)	3.77 (2.7)	4.23 (2.23)	2.99 (2.62)	3.90 (3.14)
Workplace POI (N)	44.03 (31.76)	49.25 (34.65)	31.54 (31.96)	48.72 (23.61)
Park POI (N)	0.65 (0.83)	0.62 (0.82)	0.48 (0.88)	0.84 (0.76)
Transit stop (N)	30.8 (24.12)	40.63 (30.21)	28.77 (21.46)	20.17 (5.86)
Street curvature (≥ 0)	1.07 (0.04)	1.08 (0.05)	1.08 (0.04)	1.05 (0.02)
Street intersection (N)	13.31(5.04)	14.11(5.12)	11.31(4.43)	13.35(4.72)
NDVI	0.24 (0.09)	0.28 (0.09)	0.26 (0.05)	0.17 (0.08)

Note: N = Number; POI = Point of interest; NDVI = Normalized difference vegetation index.

Table 4
Multilevel logistic models for predicting the statistical results of the healthy group (BMI<24) vs. overweight or obese group (BMI ≥24) (N = 4440).

Model predictor	Model 1			Model 2		
	OR	95% CI	P-value	OR	95% CI	P-value
Built Environment						
Population density	1.020	0.981–1.059	0.336	1.020	0.981–1.059	0.325
Land-use mix	0.963	0.931–0.994	0.022*	0.961	0.929–0.992	0.028*
Water feature POI	0.978	0.963–0,994	0.015*	0.978	0.963–0.994	0.016*
Supermarket and grocery POI	0.891	0.836–0.946	<0.001***	0.891	0.836–0.948	<0.001***
Workplace POI	1.023	0.980–1.066	0.291	1.021	0.978–1.064	0.339
Park POI	1.024	0.987–1.062	0.220	1.026	0.989–1.064	0.180
Transit stop	1.042	1.003–1.081	0.055.	1.038	0.998–1.077	0.083.
Street curvature	0.935	0.904–0.966	0.008**	0.937	0.906–0.968	0.011*
Street intersection	0.952	0.911–0.993	0.029*	0.954	0.913–0.995	0.036*
NDVI	0.950	0.913–0.988	0.013*	0.950	0.913–0.988	0.012*
Community type						
Commercial community (reference group)						
Work-unit community	1.048	1.015–1.081	0.006**	1.048	1.015–1.081	0.007**
Traditional community	1.423	1.357–1.490	<0.001***	1.423	1.357–1.490	<0.001***
Gender						
Male (reference group)						
Female				1.010	1.008–1.012	<0.001***
Age				1.097	1.096–1.099	<0.001***
AIC	96,862.40			88,985.13		
BIC	97,036.37			89,182.30		

Note: . <0.1. *p < 0.05. **p < 0.01. ***p < 0.001; N = Number; OR = Odds ratio; 95% CI = 95% Confidence interval; AIC = Akaike information criterion; BIC = Bayesian information criterion.

At built environment level, built environment factors with high relative importance also vary in three community types. In commercial community, high relative important factors are transit stop (40.08%), supermarket and grocery POI (26.48%), and street intersection (12.72%) (Fig. 5). In the work-unit community, they are street intersection (43.96%), NDVI (24.31%) and street curvature (10.61%) (Fig. 6). In the traditional community, they are transit stop (31.49%), land-use mix (27.35%), and supermarket and grocery POI (13.82%) (Fig. 7).

5. Discussion

There is strong evidence that the neighborhood-level built-environment affects the individual's bodyweight status via three major mechanisms (Huang et al., 2015; Wen and Kowaleski-Jones, 2012). However, there is scarce evidence of the effect of the community type on the bodyweight status because most studies are conducted in low- or medium-density cities in Western countries. With rapid urbanization, multiple types of community, which have distinct characteristics of the built environment, have emerged and coexisted in major cities of China. Different community types may represent different physical environments and different socioeconomic statuses of the residents, which affect lifestyle habits, such as exercise and daily dietary habits (Lei and Lin, 2021). This study is among the first to examine the effect of the community type on the individual's bodyweight status within the Chinese context. It is found that a resident's propensity to be overweight or obese is associated with the community type. Our findings provide a more nuanced understanding of the association of the built environment and the resident's bodyweight status. In addition, our study used a novel methodology that combined the strengths of the multilevel logistic model and random forest algorithm. We were thus able to consider

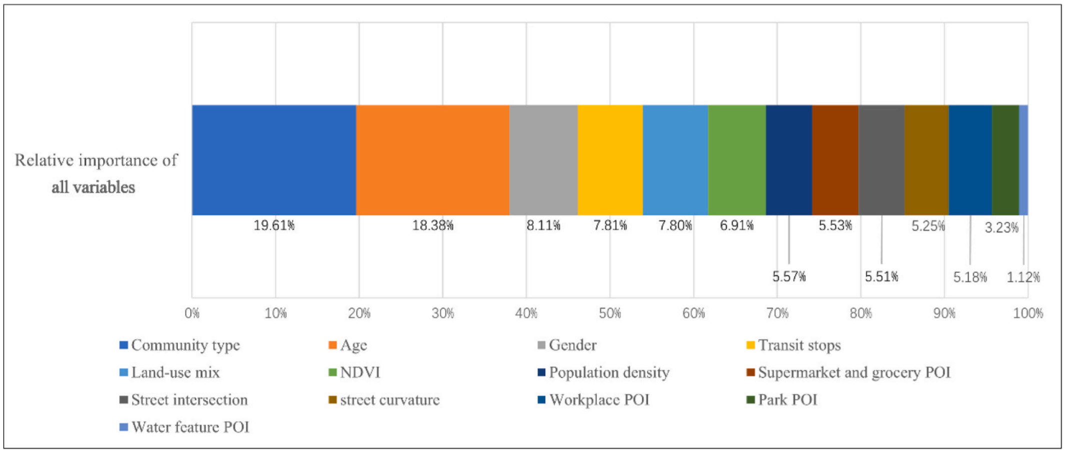

Fig. 4. Relative importance of all explanatory variables, including the community type.

Table 5
Relative importance of the significantly related explanatory variables at overall level.

Variable	Commercial community	Work-unit community	Traditional community
Age	29.59%	32.58%	47.78%
Gender	14.53%	9.17%	7.23%
Built environment	55.88%	58.25%	44.99%

Table 6
Relative importance of the significantly related built environment variables at built environment level.

Variable	Commercial community		Work-unit community		Traditional community	
	Ranking	Relative importance	Ranking	Relative importance	Ranking	Relative importance
Transit stop	1	40.08%	5	8.78%	1	31.49%
Supermarket and grocery POI	2	26.48%	6	3.16%	3	13.82%
Street intersection	3	12.72%	1	43.96%	6	3.36%
Street curvature	4	7.54%	3	10.61%	4	14.72%
Land-use mix	5	5.95%	4	9.18%	2	27.35%
Water feature POI	6	5.56%	7	<0.01%	7	<0.01%
NDVI	7	1.69%	2	24.31%	5	9.35%

both the significance and relative importance of individual variables. The new method and findings may help policymakers to develop various evidence-based interventions for different types of community.

The current results support the results of previous studies that some neighborhood-level factors of the built environment have significant associations with an individual's bodyweight status (Garfinkel-Castro et al., 2017; Li et al., 2009; Wen and Kowaleski-Jones, 2012). For instance, we find that the NDVI and water feature POI are associated with lower odds of being overweight or obese among the overall respondents, which is in line with the results of previous studies (Yang et al., 2021). It is feasible that residents in an environment with more green and blue spaces are more likely to engage in recreational physical activity (Berke et al., 2007; Cerin et al., 2013), reducing their risk of overweight/obesity.

Our research also supports that a higher land-use mix, a greater number of street intersections, and greater street curvature reduce the risk of obesity because mixed land use and well-connected streets may stimulate active travel behaviors, such as walking and cycling for transportation purposes (Jia et al., 2021; Ying et al., 2015).

Destination accessibility, especially in terms of the number of supermarkets and grocery stores, is negatively associated with the risk of overweight. Daily grocery shopping affects a resident's access to healthy food and overall physical activity level, because daily walking trips to these stores are regarded as a major type of physical activity for Chinese residents, especially for older adults (Caspi et al., 2012; Cerin et al., 2013).

In contrast to earlier findings, however, transit stop is found to be positively related to a resident's risk of overweight (Xu et al., 2021). There are two possible explanations. First, fast-food restaurants are usually distributed around bus stations in Beijing. Hence, bus stop is considered as being representative of a high-energy food environment that increases the risk of overweight. We find a medium correlation between the restaurant POI and transit stop (Pearson's $r = 0.393$, $p < 0.01$), which may support this conjecture. In addition, a previous study finds a positive association between the bus station density and the adiposity outcome because a bus station

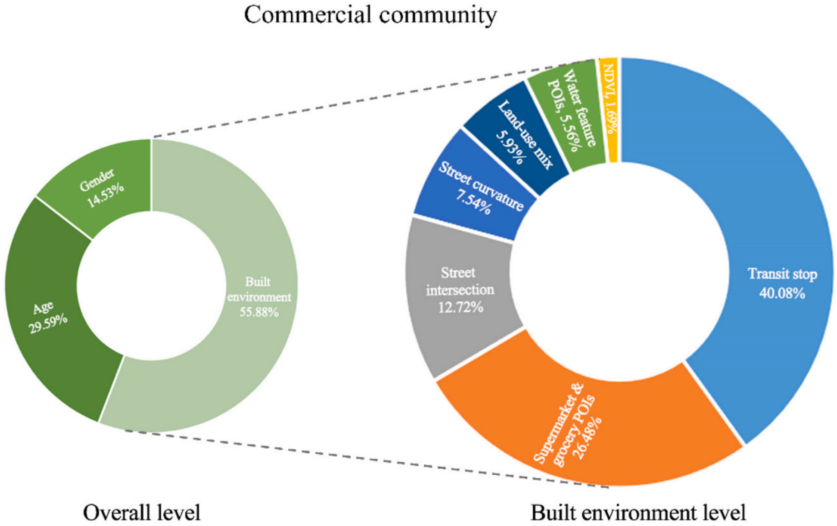

Fig. 5. Relative importance of explanatory variables in commercial community (overall level and built environment level).

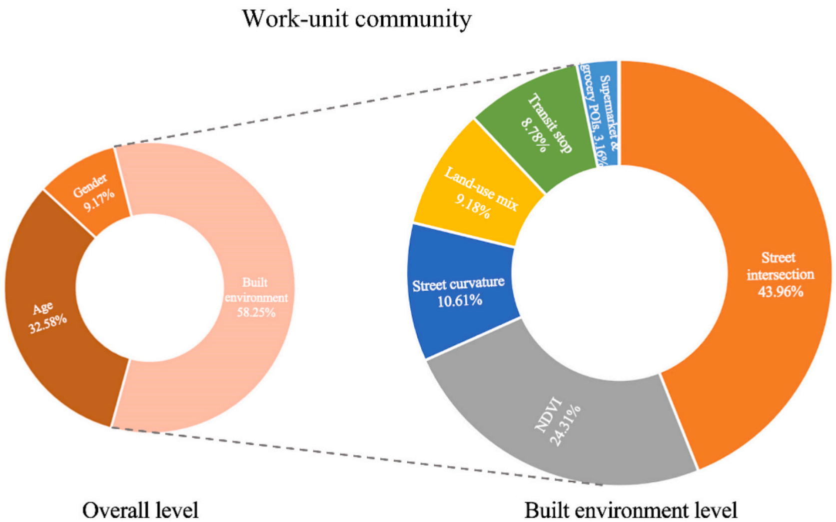

Fig. 6. Relative importance of explanatory variables in work-unit community (overall level and built environment level).

is a typical obesogenic food environment associated with a high energy intake (Duncan et al., 2012). Another possible explanation is that convenient public transportation may not be equivalent to high-frequency public transit use because of a resident's various commuting mode choices (Xu et al., 2021). Emerging transportation modes, such as ride hailing and the bicycle sharing, have changed the travel behaviors of residents in terms of taking public transport (Jin et al., 2019). The change in travel mode may moderate the association between public transportation and the resident's bodyweight status.

Our results reveal nuanced differences between the relative importance of population structure (i.e., age and gender) and built-environment factor across three community types. The respondent's age has high relative importance in traditional community (47.78%), work-unit community (32.58%) and commercial community (29.59%), which indicates population structure have important impact on the obesity risk and confirms the findings of previous studies (Giskes et al., 2011; Yu, Woo, Emrich and Wang, 2020). However, previous studies have neglected the disparities of obesity risk and built environment factor across different community types.

We also find that there are disparities of the relative importance of built-environment indicators between the three types of community. The relative importance of the built-environment variables is similar between traditional and commercial communities but differs from the work-unit community (Figs. 5, Figs. 6 and 7). Specifically, transit stop has the highest relative importance in traditional and commercial communities but low relative importance in work-unit communities. The same trend is observed for the relative importance of the NDVI in that it is low in traditional and commercial communities but high in work-unit communities. The difference may be related to the different commuting behaviors of residents in the three types of community. In China, the residents of

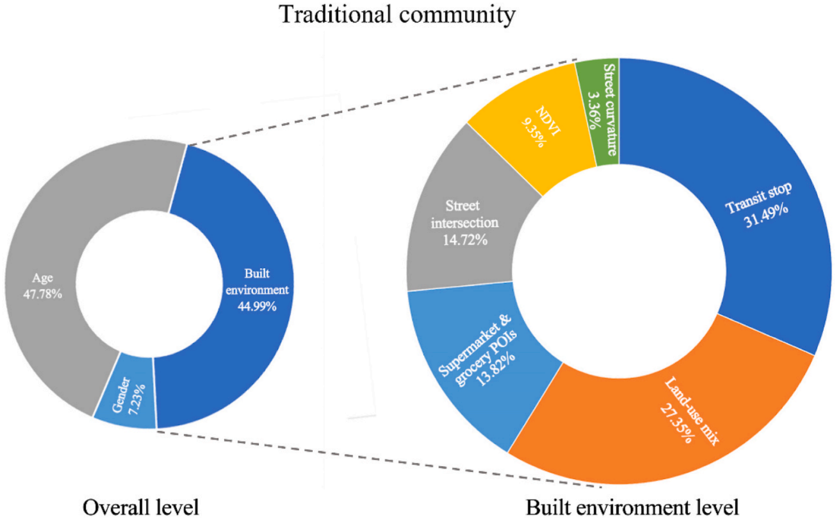

Fig. 7. Relative importance of explanatory variables in traditional community (overall level and built environment level).

a work-unit community generally live close to their workplaces and may choose to walk or cycle to and from work (Gao et al., 2016). In contrast, most commercial and traditional community residents prefer automobiles and public transportation as their primary commuting mode owing to their long commuting distances (Guan et al., 2020). Therefore, street intersections and NDVI, as two determinants of active transportation, have higher importance for residents in the work-unit community (Huang et al., 2020; Yang et al., 2019). For the same reason, transit stop, which affects the mode choice of public transportation over private automobiles for long-distance commuting trips, is more influential in traditional and commercial communities (Guan et al., 2020; Zhao and Chai, 2013).

We find that the notable built environment features of each type of neighborhood often have high relative importance. As an example, the traditional community has a higher land-use mix degree (mean of 0.80), which distinguishes it from commercial (mean of 0.52) and work-unit (mean of 0.44) communities (Guan et al., 2020; Li et al., 2012). Additionally, the land-use mix has higher importance in traditional communities (27.35%) compared with the other two community types (5.93% and 9.18%). The same phenomenon is observed for supermarket and grocery POI. The average numbers of supermarket and grocery POI in commercial, work-unit, and traditional communities are 4.23, 2.99, and 3.90, respectively. Correspondingly, the relative importance of supermarket and grocery POI for the three community types is 26.48% in commercial communities, 3.16% in work-unit communities, and 13.82% in traditional communities. This consistency between neighborhood built-environment features and the relative importance of these factors may originate from various lifestyle habits of the residents of the three community types (Li et al., 2012). This finding illustrates that there may be different mechanisms underlying the effects of built-environment characteristics on obesity risks in different types of community (Gao et al., 2016; Guan et al., 2020; Lei and Lin, 2021).

We find notable differences in the results between multilevel regression and the random forest model. Specifically, water feature POI is found to be significantly associated with the individual's bodyweight status ($p < 0.05$). However, the relative importance of water feature POI in commercial, work-unit, and traditional communities is marginal (5.56%, <0.01%, and <0.01%, respectively). Despite a low significant association between transit stop and a resident's BMI in the multilevel regression model ($p < 0.05$), the random forest model suggests that transit stop plays an important role in the three types of community; the relative importance is 40.08% in commercial community, 8.78% in work-unit community, and 31.49% in traditional community, respectively (Table 6). Similar disparity between the linear regression and random forest model is reported in previous studies (Pahlavan-Rad et al., 2020). Linear and logistic regressions are favored by researchers because these methods have easy calculation and interpretation (Smith et al., 2013), but they may oversimplify the complex relationship between the built environment and health outcomes. As a more complex regression method, the random forest has higher predictive abilities than linear and logistic regression models (Smith et al., 2013). However, the random forest has its limitations, such as poor performance on data with noise and high training and calculating costs (Pahlavan-Rad et al., 2020). In our study, we combined the strengths of the multilevel logistic regression and random forest methods. We could thus explore not only where a built-environment factor is significantly associated with bodyweight status but also the relative importance of the factor.

5.1. *Planning implications*

In the Chinese context, policies and intervention strategies for reducing the risk of obesity among residents should be tailored to meet the needs of each type of community. For a commercial community, intervention strategies of improving the accessibility of public transit and supermarkets should be implemented to encourage active transportation and a healthy food environment. The future directions of the renewal of the work-unit community are to increase street connectivity and greenery exposure, which will facilitate physical activity and active transport. The traditional community should embrace multiple interventions owing to the prevalence of its socioeconomic disadvantage (Guan et al., 2020). Interventions, such as land-use mix, public transits, and street intersections should be considered.

For all the high-density cities, this article provides policymakers an effective decision support framework to identify the most influential built environment factors related to resident's obesity risk. Based on the framework, tailored policies and planning interventions may contribute to reduce resident's obesity risk in local urban context. Besides, this paper further confirmed the irreplaceable role of active transport in enhancing physical activity level and access to a healthy food environment (Bassett et al., 2008; Brown et al., 2017a; Hall and Ram, 2018). Hence, urban planners should cast an eye on the relevant strategies, i.e., enhancing the density public transit network and building walking-friendly community, during the urban renewal procession to reduce obesity risk.

5.2. Limitations

There are limitations to the present study. First, it is a cross-sectional study; therefore, the causal relationship between the neighborhood-level built environment and a resident's risk of overweight and obesity cannot be determined. Future studies could conduct quasi-experimental research by, for example, comparing the BMI changes of residents before and after community renovation (Aarland et al., 2017) or residential relocation (Boone-Heinonen et al., 2011). Second, the study used a 800-m street network buffer around a residence as the basic research unit. However, ignoring the activity space outside the buffer (i.e., ignoring activities other than those taking place with residential neighborhoods) may result in the *uncertain geographic context problem* and lead to inaccurate results (Zhao, Kwan and Zhou, 2018). Further studies need to accurately delineate an individual's activity space and better define built-environment exposure. Third, the study did not consider socioeconomic status data (e.g., education, household income, and family structure), which were unavailable. Future studies could collect such information through a questionnaire or survey.

6. Conclusion

We estimated the relationship between the characteristics of a built environment and the risk of overweight and obesity for 4,440 respondents in three types of community (i.e., commercial, work-unit, and traditional communities) in Shijingshan district, Beijing, China. Our findings clearly indicate that the community type has a significant association with the risk of overweight. Meanwhile, the use of a random forest model revealed notable disparities in the relative importance of population structure and built-environment characteristics between the three community types. Our findings highlight the need for tailored planning policies and intervention strategies for different types of community to reduce the risk of overweight and obesity among residents.

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Credit Author Statement

Yuxiao Jiang: Conceptualization, Methodology, Writing – original draft, Revising and editing. Shanchao Wang: Data collection, Data curation, Visualization, Writing – original draft. Lijian Ren: Conceptualization, Writing – review & editing. Linchuan Yang: Writing – review & editing. Yi Lu: Supervision, Methodology, Writing – review & editing

Appendix A. Definitions of the outcome and independent variables

	Variable	Definition	Category
Outcome variable			
BMI	Overweight or obese	1 (BMI $\geq$24)	
	Healthy	0 (BMI<24)	
Independent variables			
Individual level (level 1)	Age	Age of the participant	
	Gender	Male (reference group), Female	
Neighborhood level (level 2)	Population density (N/km^2)	Population density of each neighborhood buffer zone	Density
	Land-use mix ($\geq$0)	The ratio of different land-use types in each neighborhood buffer zone	Diversity
	Water feature POI (N)	The number of water features with an area of more than 500m^2 in each community buffer zone	Destination accessibility
	Supermarket and grocery POI (N)	The number of corresponding POIs in each neighborhood buffer zone (acquired from http://map.baidu.com)	
	Workplace POI (N)		
	Park POI (N)		
	Restaurant POI (N)		

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	Variable	Definition	Category
	Public service POI (N)		
	Transit stop (N)	The number of bus stops in each neighborhood buffer zone	Distance to transit
	Street curvature (≥0)	The average cumulative angular curvature along each street in each neighborhood buffer zone, in degrees: $d_{\theta}(y)$	Design
	Street intersection (N)	The number of street intersections (three or more streets) in each neighborhood buffer zone	
	NDVI	Over-head greenery level of each neighborhood	Urban greenery
	Community type	Commercial community (reference category), work-unit community, traditional community	

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