The Difference of Contribution of Urban Built Environment Factors to Obesity of Residents: A Case Study from the Shijingshan District of Beijing

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Abstract

Background

The obesity rate of Beijing residents has been rapidly increasing in the past decades. The incidence rate of diseases caused by obesity is high, and resident health is a concern. According to public data and published studies, obesity may be related to the urban built environment.

Methods

In this study, a data set of "resident health–urban built environment" based on the data of surveying and mapping in the Shijingshan district of Beijing and the registration data of obesity status from top medical institutions in Beijing is developed. The data of the urban built environment includes five factors: the economic value of location, mixture of land use, facility layout, spatial characteristics of streets, and subjective evaluation data of residents. Additionally, a multi-dimensional judgment matrix of obesity of residents and built environment indicators is established. The random forest algorithm of machine learning is used to classify the data set, and the correlation and contribution of the influence of each environmental factor on the obesity are judged.

Results

For all communities in the Shijingshan district, the street betweenness and street curvature make the largest contributions to obesity among all spatial characteristics, whereas the number of parks and water-related sceneries in the living environment contributes the least.

Conclusions

The calculated contributions of different environmental factors to obesity can be directly employed to promote a healthy lifestyle. On the premise of intervention cost-saving, similar effects can be achieved by improving the spatial environment of streets and layout of facilities rather than applying intervention measures of the overall change.

1. Background

Obesity is a major global public health concern with an annually increasing prevalence rate in most urban areas(1). China has recorded the highest number of obese individuals, with an obesity rate as high as 25.9% and an overweight rate as high as 33.4% in Beijing in 2018 (2). The high prevalence is also associated with a considerable economic burden of about 1.1 trillion yuan each year (3). Reforms in the country have increased employment opportunities in the past 40 years, with a noticeable change in the urban environment as more people migrate, affecting the health of residents (4, 5).

Evidence suggests that the environment plays a central role in causing obesity, mostly through its conducive or inhibitive effects on physical activity and diet (6, 7). However, studies in different countries

and regions have revealed that different cities have varied effects on obesity prevalence, with significant differences observed even between neighboring communities and neighboring provinces (8). Residents living in communities with higher land-use density, higher land-use structure, fewer crimes, higher traffic safety, and more access to entertainment facilities typically prefer physical activities to sedentary indoor activities, such as watching TV, surfing the Internet, and playing computer games (9). Of the surveyed environmental characteristics, those most consistent with the body mass index (BMI) were neighborhood socioeconomic status, walking environment, and opportunities for activities in leisure facilities (10).

The correlation between the urban built environment and obesity is conspicuous (1, 11–13). However, differences in ethnicity, culture, social development, economic development, and many other factors contribute to the uncertainty of overweight and obesity risk of a specific population. For instance, the influence of the built environment on obesity may vary according to individual characteristics in residents belonging to different groups. As residents grow older, they are less likely to exercise and more likely to spend their time indoors and have lesser interaction with the built environment (14). Generally, women are less physically active compared with men (15–17). Moreover, the poor built environment and less safe communities make residents more likely to stay indoors, thus increasing the possibility of obesity (14). In the process of using nearby facilities, more abundant service facilities (services and entertainment facilities) and natural facilities (attractive open space and rivers) can enhance people's willingness to travel, which is more conducive to maintaining a healthy weight of residents (18). Street characteristics can also affect people's obesity. According to a Canadian survey, obesity or overweight in a particular area was negatively correlated with street intersection density (i.e., the ratio of street intersections in a certain area) (19). Personal perception of the environment, including the safety perception of the venue, evaluation of the venue (or street) facilities, and evaluation of personal health, affects the residents' obesity (20).

Another challenge is the measurement of the built environment. There are no fixed standards for description of the built environment (21), and it is usually measured in terms of the physical space environment, economic environment, social culture, and political environment in the ideal context of the built environment research (22–24). Common measures are population density, the mixture of land use, the layout of service facilities, and street space. The characteristics of the physical space environment are that they can be evaluated subjectively and measured objectively. Typically, the subjective evaluation is a self-reported perception of the environment (25). However, the objective measurements are directly collected in the field or calculated from available land-use data sets. The built environmental factors may directly or indirectly affect the risk of obesity (which may vary between individuals) (26).

In this study, we included the experimental data set of subjective evaluation and objective measurement. The published studies have applied different measurement methods (27–36) for the built environment, which is decomposed into specific elements that can be described quantitatively to facilitate subsequent calculations and standards for implementation of future countermeasures. The quantified environmental indicators were of 5 categories, and 15 sub-categories of variables possibly related to obesity (7, 12, 30, 34, 37, 38). The five categories are community demographic characteristics (to describe the street-level

population); the economic value of a location (to measure the social status); the mixture of land use (the mixture of POI points, meaning the level of the mixture of land use) and facility layout (to measure the accessibility of entertainment facilities); spatial characteristics of streets (to describe the quality of physical space of streets); and subjective evaluation of residents for space use of streets, as is presented in Table 1. Each of the statistical data were obtained from official statistical channels in China. Detailed information on health and built environment variables of 15 residents included in this study is presented in Table 1. The health data of BMI, age, gender, and home address were obtained from the health registration data of a certain leading hospital in Beijing. Subjective evaluation data were obtained from investigation and interview and consisted of the street walking facility score (subjective evaluation of whether the street is suitable for walking) and the street cycling facilities score (subjective evaluation of whether the street is suitable for riding) (11, 39).

In this study, we aimed to determine the effect of the built environment on obesity in the residents of the Shijingshan district of Beijing through subjective evaluation and objective measurement of BMI and built environment. We mainly focused on the ranking of the contribution of each index in the built environment to obesity.

2. Methods

Shijingshan district, a main urban area in Beijing, was selected as the research area in this study. The district is located in the west of Beijing (Fig. 1), with an area of 84.5 km² and a population of 590,000 (in 2018). The basic data used in this study to evaluate the built environment of the city were obtained from an electronic map of Beijing

According to central road lines, natural landform, and boundaries of communities where the residents live, the research area was divided into 89 map sheets, which were saved as files in the format of shapefile for backup (Fig. 2). In total, 8,941 health data of residents was collected in the research area, with the age of the residents being 18 to 99 years. Considering the citizen's privacy and relevant laws and regulations, the only necessary information was collected and anonymized. The information obtained were address, height, weight, age, and gender.

Residents were classified based on obesity, measured using the traditional BMI, calculated by $\text{weight}/(\text{height})^2$, as is presented in Table 2. BMI is a commonly used global standard for measuring the fat content and health of an individual.

2.2 Quantitative calculation method of the urban built environment

The network distance coverage of the community and the daily life circle was determined. According to Traffic Analysis Report of Major Cities in China in 2018 (40) and the concept of daily life circle of 15-min travel in *Code for Planning and Design of Urban Residential Areas* (2018 edition), we determined that the

travel radius starting from the geometric center of the residential area was 700 m. The boundary of the residential area scuttling through a certain large map website in China was imported into the ArcGIS, and the travel radius was expanded according to the network distance of 700 m (Fig. 3). The map within the research scope was divided, and a total of 80 research samples were obtained, as is shown in Fig. 4.

The role, processing methods and data sources of other research data are shown in Table 3.

3. Results

3.1 Spatial statistical analysis

A kernel density processing was performed on the resident samples with BMI > 28 kg/m². Figure 5 is a scenario after visualization analysis. A comparison of spatial distribution revealed a significant spatial distribution correlation between the spatial distribution of obese people with BMI > 28 kg/m² and the distribution of residential areas.

3.2 Statistical data analysis

The classification method of machine learning was used to judge the contribution of various elements in the built environment to obesity. In the past, statistical methods such as factor analysis have often been used in multivariate factor calculation and analysis. The systematic error that requires artificial abandonment and judgment of variable importance can be avoided with the machine learning approach, thus leading to a higher accuracy to the classification calculation of multivariable factors. As for the selection of the machine learning algorithm, the random forest algorithm that could perform automatic machine classification was selected to rank the contribution of the environmental factors toward obesity. Using the data set of the residents' health data and the built environment indicators, after adequate training of the model, we performed a large-scale machine judgment on the role of community environment in obesity.

The two key parameters in the model *mtry* and *ntree* were defined to calculate the contribution. *mtry* determines the classification accuracy to a certain extent and specifies the number of variables used in the binary tree in the node. In contrast, *ntree* refers to the number of decision trees, i.e., the number of candidate spatial variables for the split node of the decision tree. According to the empirical data of the same scale data and the training value of the random forest model, the final calculation parameters (*mtry* = 7; *ntree* = 2000) were determined in this study. The relationship between the error distribution and *ntree* is presented in Fig. 6.

First, we summarized all the environmental factors, and each of the contributing factor was calculated by the model according to its influence on the obesity of residents, and the results are provided in Table 4. The results as visualized using the R language are presented in Fig. 7.

Typically, the residents' rating of bicycle facilities, subway coverage, the density of walkable street intersections, and the number of walkable street intersections were positively correlated with BMI,

whereas other environmental factors were negatively correlated. Among all the negatively correlated factors of the built environment, the street betweenness made the highest contribution to obesity, at 19.26, and the presence/absence of a water-related scenery in the daily life circle made the lowest contribution, at 0.41. The spatial characteristics of streets had the greatest influence on the obesity of residents, whereas the effect of street betweenness and street curvature on obesity was 19.26 and 18.44, respectively. The influence of mixture of land use on obesity varied, whereas that of the mixture of land use from POI and count POI in the daily life circle were 18.31 and 13.47, respectively. The influence of cultural and social status and the contribution of average housing price and property management fees of core communities to obesity were 18.18 and 17.8, respectively. The contribution of community demographic characteristics to obesity was generally not high, among which three indicators of total population of the street where the households are located, total number of houses in the daily life circle, and street level of population density made contributions of 14.81, 12.17, and 8.86, respectively. Among all the influencing factors, the last factor was facility layout, and the contributions of subway coverage, number of water-related sceneries, and coverage of parks in the daily life circle to obesity were 8.63, 3.66, and 0.41, respectively.

4. Conclusions

In this study, the popular machine learning algorithm was used to determine the relationship between variables. The spatial algorithm was introduced to process the medical data so that the information encrypted in the data was explored deeply. The findings of this study can help reform old residential areas to improve the health status of the residents and effectively control the reformation investment. During the reformation, it is more beneficial to invest in the quality improvement of street space inside and outside the residential area, upgrade the property and quality of the residential area itself, and implant composite functions of the street.

The obesity rate of residents in the Shijingshan district of Beijing was 26.87%, higher than the average level of 25.8% in Beijing. Several variables of individual-level and urban built environment levels associated with obesity in the Shijingshan district were verified in this study. The results revealed that the environmental variables, that is, the economic value of location, mixture of land use and facility layout, street spatial characteristics of streets, and subjective evaluation of residents, had an impact on the obesity of residents living in the environment. Among the factors, street betweenness and street curvature contributed most to obesity. In contrast, coverage of parks and the number of water-related sceneries in the daily life circle among the factors of facility layout contributed the least.

4.1 Analysis of possible causes

In terms of the street space index, street betweenness and street curvature, respectively, represented the urban vitality and safety of a street in a small area, which is in line with the published results. The higher the vitality, the lower the vehicle speed on the street, and the lower the resident BMI. The other two elements of the street space index, i.e., the density and the number of walkable street intersections, were

positively correlated with BMI, which is different from the findings of the published studies. The possible reason is that increased intersection density and number result in considerably low-speed motorized traffic. The frequent occurrence of air quality problems in China over the past years has attracted the residents' attention. Streets with more intersections imply more low-velocity motorized traffic and more air pollution, which affect the physiological and psychological indicators and thereby the weight of the residents. This finding is consistent with the conclusions of Jerrett et al., who pointed out that air pollution affects the bodyweight of the residents on a micro-scale, increasing the BMI (41).

In terms of the economic value of a location, the findings are consistent with the conclusions of previous studies conducted outside of China. The socioeconomic status factors represented by high average housing prices and high property management fees of core communities reduce the obesity of residents. For mature residential areas, residents prefer community activities, for a sense of belonging. Because of objective factors, such as property management fees, the mature residential community is more attractive to the residents than the external environment, and the internal environment can promote a specific behavior, which is particularly obvious in a community with ample public space (42).

In terms of community demographic characteristics, there are more residents in the daily life circle. Higher population density leads to higher BMI, which is in conflict with some existing research results from Hong Kong. This difference may be attributed to the low overall population density of Beijing compared with the ultra-high population density of Hong Kong and varied natural conditions of mountainous regions and the multi-step natural height difference of Hong Kong. The higher the street walking facility score, the lower the BMI. According to residents' psychological activities, a higher street walking facility score indicates that the residents are more satisfied with the street environment, and they are more inclined to go to the street, which increases physical activities and reduces BMI.

In terms of the mixture of land use and service facilities, the coverage of parks and the number of water-related sceneries in the daily life circle contributed the least to BMI. The city waterfront environment generally appears with the green space park, which is consistent with the conclusions of previous studies that the park coverage reduces the obesity rate. However, the contribution of these two factors was slightly lower in this study. The higher the mixture of land use, the smaller the obesity degree of residents. High mixture of land can provide more attractive facilities for residents' travel, such as shopping malls, cultural facilities, and medical facilities. Rich facilities can passively reduce obesity by attracting residents to increase physical activities, which is consistent with previous research conclusions.

A unique feature in this study was to describe the physical space environment quantitatively by a variety of objective measurement indicators of the urban built environment. Higher reference values were obtained with the same method of quantitative measurement, but when fewer variables were used in two previous studies (15, 43). Therefore, in this study, we found a unique contribution of the built environment to prevent obesity. Unlike Alvarado's study (a single composite variable was used to describe factors detrimental to health in the neighborhood), our study reports the influence of built environmental factors

on obesity in 5 major categories and 15 sub-categories, thus providing more direct evidence for future policy intervention on obesity.

It is also important to use health data such as the height and weight of residents from medical institutions. The sample size of the health data in medical institutions is considerably large ($N = 8941$) for making a greater number of statistical judgments, performing hierarchical analysis to determine the relationship between different urban built environmental factors and obesity, and creating a map to visualize the high incidence area of obesity to facilitate subsequent health intervention policies. Meanwhile, the introduction of professional medical data can effectively avoid the bias of self-reported survey and improve the accuracy of the research. In the follow-up study, more variables can be introduced to the environmental measurement to test the contribution of different built environmental factors to obesity and to analyze the change in weight when residents of all ages use the same environment or different environments through more detailed statistical analyses. Moreover, we will continue to cooperate with medical institutions to provide operational information for evidence-based intervention plans to promote physical activities and a healthy diet through continuous health observation data and continuous change data of the built environment (44).

4.2 Discussion

It is possible to identify the obesity factors in cities for a large number of residents by the machine learning algorithm. Most international studies have focused on the reduction of the obesity rate by changing the physical environment of residential areas. In this study, we suggest that the obesity of residents can be reduced by increasing the street betweenness and connectivity and expanding the types and quantity of various facilities to ensure the mixture of functions in the daily life circle.

4.3 Limitations

Multiple dimensions of micro-urban built environment data were used in this study to explore factors possibly affecting BMI. However, there were certain limitations for the study:

1. Because of data confidentiality, the geographic data used in this study are one-time data, and no comparable historical data can be obtained. Therefore, this study fails to draw conclusions that can be compared vertically. In addition, because lack of socioeconomic status of the family (45), we use the average housing price and property management fee to describe this characteristic. However, due to the residents' preferences, it is possible that the residents are reluctant to move out of the old residential areas because of the nostalgia for the old community, even if their income level has increased.
2. The number of built environmental factors listed in this study may be insufficient. Although 15 factors that possibly lead to obesity have been listed, several other factors that may be related to the obesity, such as urban built environment factors in the working place of residents, factors of food supermarkets near residents' working places, and residents' travel behavior in non-residential areas, have not been listed.

3. During geocoding of the residents' health registration data, certain data were discarded because of indistinct registration. Several health data were filled in by physicians according to the oral account of residents during registration. Therefore, abbreviations used for such recordings make subsequent geocoding highly difficult because some of the abbreviated addresses may represent multiple communities in the region, and the environment is highly different. To ensure the complete accuracy of the data, unrecognizable data have to be discarded to ensure the accuracy of all the registration data sets, which results in sample size reduction.

This study may have implications for the design of policy interventions to reduce obesity in China. Although the object of this study is Shijingshan, the calculation method of urban built environment and conclusions can be extended to most big cities in the north. Improvement of the calculated obesity contributors of environmental factors can be used to directly promote a healthy lifestyle. According to our results, an appreciable reformation effect can be achieved on the premise of intervention cost saving by the improvement of street environment and abundance of commercial and service facilities in the daily life circle rather than overall intervening reformation.

Abbreviations

BMI: Body mass index

mtry: Number of variables available for splitting at each tree node (Random forest algorithm term)

ntree: Number of trees to grow (Random forest algorithm term)

%IncMSE: The Percentage Increase In Mean Squared Errors (Random forest algorithm term)

IncNodePurity: The total decrease in node impurities from splitting on each variable (Random forest algorithm term)

POI: Point of interest

Declarations

Ethics approval and consent to participate

Consent for Publication

All authors have contributed equally and approved the submitted manuscript in its current form.

Availability of data and material

All data and materials in this manuscript can be shared, but subject to confidentiality agreements, all original data cannot be shared.

Competing interests

The authors have no conflicts of interest to declare.

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Authors' Contributions

Conception, Shanchao Wang; the acquisition, Lijian Ren, Yingxia Yun; analysis, Shanchao Wang., Chao Ma and Jie Wang; interpretation of data, Jie Wang, Lijian Ren, Yingxia Yun; the creation of new software used in the work, Shanchao Wang; writing—original draft preparation, Shanchao Wang, Chao Ma., writing—review and editing, Shanchao Wang, Lijian Ren, Yingxia Yun.

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Tables

Table 1

Indicators	Classification	Variable explanation	Scheme layer	Serial number	Data source
Objective measurement	Demographics	Describe the residents' obesity	BMI	1	Hospital records of residents' health registration data
		Age	Age	2	
		Gender	Gender	3	
		Home address	Home address	4	
	Community demographics	Describe the street-level population	The total population	5	Beijing statistics yearbook 2018
			Total number of houses	6	
			The street level of population density	7	
	The economic value of location	Measure of social status	Property management fee	8	A large Chinese map
			The average price	9	
	Mixture of land use	POI point of mixed and	Count POI	10	
		mixed land-use degrees	Mixture of land use from POI	11	
	Facility layout	Measure the accessibility of entertainment facilities	Coverage of parks	12	Beijing digital map
			Coverage of water-related sceneries	13	
			Subway coverage	14	
	Street space characteristics	Describe the quality of the material space streets	Density of walkable street intersections	15	Beijing digital map
Data Source: Author compiled the literature review					

Indicators	Classification	Variable explanation	Scheme layer	Serial number	Data source
			Number of walkable street intersections	16	
			Street curvature	17	
			Street betweenness	18	
Subjective evaluation	Subjective evaluation	Measure the streets' suitability of subjective evaluation on foot	Streetwalking facility score	19	Fieldwork to collect
		Measure whether the street cycling subjective evaluation	Street cycling facilities score	20	
Data Source: Author compiled the literature review					

Table 2
Classification method for assessing obesity

BMI (kg/m ²) Classifications	WHO Standard	Asian Standard	Chinese Standard	Risk of Comorbidities
Underweight	< 18.5			Low (but there may an increased risk of other clinical problems)
Normal	18.5–24.9	18.5–22.9	18.5–23.9	Average
Overweight–Obese	≥ 25	≥ 23	≥ 24	Increased
Overweight	25.0–29.9	23–24.9	24–27.9	Mildly increased
Obese class I	30.0–34.9	25–29.9	≥ 28	Moderate
Obese class II	35.0–39.9	≥ 30	—	Severe
Obese class III	≥ 40.0	Very severe		Very severe
Data source: Website of China CDC.				

Table 3
The role, processing method and data source of other data

Research Data	Role	Processing Tools	Data Source
Demographics[1]	Geocoding to calculate BMI and health information of the urban residents	ArcGIS geocoding	A first-tier hospital in Beijing
Community demographics	Determine the community Daily Life Circle number, population density, and other characteristics	Statistical tools	Beijing Statistics Yearbook 2018
Economic value of a location	Determine the economic value of a daily life circle core community location	Statistical tools	Web crawler crawl China, a large property transactions 2018 residential information website
Mixture of land use and facility layout	Calculation within the scope of daily life circle Land mix and other properties	ArcGIS Geographic statistical tools	Web crawler crawl, a large map of Chinese electronic map data and POI data up to 2018
Spatial characteristics of streets	Quantitative life space indicators of a road network	In ArcGIS sDNA plug-in	Figure as a road map to 2018 Beijing road information
Subjective evaluation	Record residents' subjective evaluations of street walking facilities and street bicycle facilities	Statistical tools	Interview and questionnaire survey
<p>Data Source: Author collation.</p> <p>[1] Table note: When measuring the demographic characteristics, we use ArcGIS to geocoding the health data after ignoring the invalid data, the number of final data is 8635 which covers 80 residential area, and 1.51% of the total population of Shijingshan district 1. Statistics BMBo. 2018 BEIJING STATISTICAL YEARBOOK: National Bureau of Statistics; 2018..</p>			

Table 4
The contribution and correlation ranking of each impact factor

Environmental factors	%IncMSE	IncNodePurit	Correlation	Contribution
Street betweenness	19.26	99.76	-1	-19.26
Street curvature	18.44	110.81	-1	-18.44
Mixture of land use from POI	18.31	103.35	-1	-18.31
The average price	18.18	119.8	-1	-18.18
Property management fee	17.8	90.21	-1	-17.8
Total number of houses	14.81	126.88	-1	-14.81
Street walking facility score	14.78	51.67	-1	-14.78
Count POI	13.47	60.85	-1	-13.47
Street cycling facilities score	12.84	50.4	1	12.84
The street level of population density	12.17	36.47	-1	-12.17
The total population	8.86	30.43	-1	-8.86
Subway coverage	8.63	21.85	1	8.63
Density of walkable street intersections	7.55	7.55	1	7.55
Number of walkable street intersections	7.21	7.21	1	7.21
Gender	6.27	256.03	-1	-6.27
Coverage of parks	3.66	12.1	-1	-3.66
Coverage of water-related sceneries	0.41	11.5	-1	-0.41

Figures

Figure 1

Location map of the Shijingshan district. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Network Radius

Euclidian Radius

Figure 3

Network Radius and Euclidian Radius

Figure 6

Relationship between error distribution and ntree

Different color meaning in **Figure 7**

Community demographic characteristics	Economic value of location	Mixture of land use and facility layout	Spatial characteristics of streets	Subjective evaluation
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Figure 7

Contribution of built environment factors to obesity in ascending order of the absolute value