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Nonlinear relationship between the urban form and street vitality: A data-informed approach involving twelve Chinese cities

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Abstract

The relationship between the urban form and urban vitality has been widely discussed over the past few decades. Nevertheless, due to the limitation of available fine-scale urban data and analytical methods, previous empirical studies have mainly focused on mesoscale urban morphological characteristics within the scope of a single city, while micro-scale analyses among different cities are rare. In addition, most researchers adopt traditional linear or pre-defined regression models while ignoring the nonlinear effects of urban form characteristics. To address these two gaps, this study examines multi-source big data to measure multidimensional urban form characteristics from both the top-down and human-scale perspectives. Taking the streets of 12 Chinese city old districts as samples, this study uses a gradient promotion decision tree model to examine the irregular association between the urban form and street vitality. The explanations for the model indicate that: (1) Compared with the functional and human-scale morphological characteristics, the mesoscale morphological characteristics, especially the street intersection density, block size, street density, building density, and floor area ratio are dominant contributors to street vitality; (2) There is a nonlinear relationship between some urban morphological characteristics and street vitality and their associations change drastically past some thresholds of urban form attributes.

Keyword: *street vitality, urban form, nonlinear, multisource data, human-scale*

Introduction

Urban vitality can facilitate human activities and social interactions (Jacobs, 1961) and contribute to sustainable urban development (Hasan et al., 2013). Jacobs pointed out that the activities of pedestrians on the street are the main source of vitality, and based on this, she also summarised characteristics of the urban form necessary to create street vitality. Her views are regarded as the benchmark for understanding urban operations today (Downs, 2005; Klemek, 2007). Meanwhile, many studies have used more accurate data and analytical methods to verify the effect of the urban form on vitality. For example, Sung et al. (2015) and De Nadai et al.(2016) test the four conditions, i.e., mixed-use, small blocks, buildings diverse, sufficient dense concentration of people and buildings, that Jane Jacobs proposed to promote life in a city. In addition, the demographic and socio-economic indicators (Long and Huang, 2019), as well as the human-scale morphological indicators based on the visual measurement of streetview (Ye et al., 2019) are also included in the relevant research.

However, there are many controversies regarding the conclusions of the relevant empirical studies, primarily concerning the heterogeneity of the research objects, which leads to limitations in the research conclusions. Moreover, these studies often assume that the urban form and street vitality follow a predefined relationship, understating the associations with urban form variables and offering erroneous implications for planning practice (Wu et al., 2019a). As a response, this study applies the gradient boosting decision trees (GBDT) approach to the data from 12 cities to address the following two questions: (1) What are the collective influence of the urban form and the relative importance of different dimensions of environmental characteristics? (2) Do urban form variables have nonlinear or threshold effects on street vitality?

Background

In recent years, machine learning models have realized a stronger predictive power, especially when combined with a wider range of higher-accuracy data, which makes it possible to analyze the urban form from both top-down and human-scale perspectives (Ye et al., 2019). Meanwhile, with the emergence of location-based service data, determining the relationship between spatial behavior and the built-up environment on a large scale has become more tractable (Zeng et al., 2018).

In terms of the capacity to illustrate non-linear relationships between variables, the GBDT method has been increasingly adopted in the research field of urban form and travel behavior (Ma et al., 2017; Wu et al., 2019b). Identifying the nonlinear effects of land-use characteristics can not only help planners make better decisions but also better inform planners of the range of effective influence of these variables (Ma et al., 2017).

Recently, Yang et al. (2021) and Xiao et al. (2021) explored the nonlinear relationship between the urban form around a subway station and urban vibrancy. In this respect, our study can be seen as a response to the increasing trend of exploring nonlinear patterns in urban forms and human behavior studies.

Methodology

Study area and sample selection

To reflect the representativeness of the selected 12 cities, they were selected from six geographical regions at different stages of economic development in China. First, based on the remote sensing monitoring database of typical urban expansion in China from 1972 to 2020 released by the Institute of Chinese Academy of Sciences, old urban areas built before 1970 in the 12 cities were selected. According to the size of the urban built-up area, a community area ranging from 12ha to 5ha was selected, within which the street sections were extracted as the sample.

Data and variables

Although the concept of street vitality is highly diverse, the intensity of street activity has been widely recognized as a comprehensive measure of street vitality (Sung et al., 2015; Delclòs-Alió et al., 2019).

Table 1 presents the variables used in the study. The survey included a list of socioeconomic and demographic characteristics that served as control variables. Since the urban form involves multi-scale (i.e., city, region, and street) and multivariate(Shen et al., 2018), it is measured by three-dimensional characteristics, including functional, mesoscale morphological and human-scale morphological characteristics.

Table 1. Variable Descriptions.

Major	Middle	Variable	Description	Data sources	Mean	*SD*
Street activity intensity		SAI, people/acre	Daily summary of street activity population density within 100m from the street centreline to both sides of the buffer zone	Mobile location service data	118.75	58.19
City	city level	12 cities classification	Baotou, Beijing, Chongqing, Chengdu, Guangzhou, Guiyang, Hefei, Ningbo, Wuxi, Wuhan, Urumqi, Yinchuan	China's urban statistical yearbook data in 2019	-	-
Demographic and socio-economic		urbanisation rate, ratio	The proportion of urban construction land area in the urban area		13.14	-
		per capita GDP of the city, yuan			160433	-
		the proportion of GDP in the tertiary industry, ratio			61.29	-
		per capita GDP of the selected urban area, yuan			112407	-
	street level	population density, people/per pixel			253.50	165.75
		Housing price, yuan/m²	The average price of commercial housing adjacent to the street	Anjuke housing agency	29216.55	6214.72
Meso-scale Morphological	length	street length, m		Building and road network data from Baidu map	172.02	102.42
	density	street density, counts/acre	Road intersections, buildings, and road density within 300m around the street		0.59	0.12
		building density, ratio			0.33	0.11
		street density, km/km²			12.85	3.44
	intensity	block size, acre	Average scale of adjacent blocks		96549.79	59942.52
		Floor Area Ratio	The average plot ratio of adjacent blocks		0.88	0.38
	street network accessibility, counts	walking accessibility	Crossing degree of the street section when calculating the road network of 400m, and 1200m around the street	The point of interest data from Amap	304.21	256.84
		riding accessibility			6357.87	5823.16
		vehicle accessibility			5800849	17078065
Functional	function	functional density, counts/m	The ratio of the total number of POI to the street length within 55m around the street section		0.64	0.51

		functional diversity, entropy	The entropy number of the function point of the block within 55m around the street		1.68	0.38
	public facilities accessibility, counts	primary school accessibility	Number of primary schools, bus stops, and kindergartens within 500m buffer zone around the street		2.06	1.39
		bus stop accessibility			7.39	3.06
		kindergarten accessibility			3.21	1.93
	commercial facilities availability, ratio	living facilities	The proportion of living, shopping, catering, sports, and leisure facilities within 55m around the street in the total number of street function points		0.15	0.08
		shopping facilities			0.26	0.15
		catering facilities			0.15	0.10
		leisure facilities			0.02	0.03
Human-scale Morphological	Visual form elements in streetscape, ratio	street facilities	The average proportion of the element pixels of facilities, greening, beyond the sky, vehicles, and motor vehicles, pedestrians, and sidewalks in the streetscape image, based on the streetscape image data of every 20m interval on the street section centreline	Streetview image data from Google map	0.32	0.14
		vegetation			0.22	0.13
		enclosure			0.91	0.06
		motorisation			0.33	0.07
		pedestrians			0.03	0.02
	spatial scale	aspect ratio	The average ratio of the height of buildings on both sides of the street to the distance between them		3.07	5.46
		nearline rate	Average stringing rate of buildings within 55m on both sides		0.68	0.34

Modeling approach

This study employed the GBDT model to explore the association between urban form characteristics and street vitality. The basic principle is to classify samples into sub-groups through decision trees, build many single decision trees, and then combine the results of these decision trees. Compared with traditional multiple regression and discrete choice models, the GBDT model does not require the response to follow any assumption, and it can accommodate variables with missing values, handle multicollinearity better, and offer more accurate predictions (Ding et al., 2018).

We used the “sklearn” package in the Python to estimate the GBDT models. To obtain robust model results, we set the number of estimators to 2400 and the learning rate to 0.01 and used a ten-fold cross-validation procedure to address potential overfitting. Specifically, the sample was divided into five subsets. The model was fitted using four different subsets (80% of the data) and validated by the remaining subset (20% of the data), repeated five times. The mean square error of the final model was 1384, and R^2 was 0.76. We then generated the relative importance of predictors and partial dependence plots (PDPs) for further analysis.

Results and discussions

The relative importance of independent variables in predicting Street Activity Intensity (SAI)

Table 2 presents the relative importance of all independent variables in predicting SAI, whose sum is 100%. The ranking was derived based on their relative importance. As the control group, the demographic and socioeconomic variables have a certain importance, accounting for 31.6%. In contrast, urban form variables generally play a more important role in predicting SAI (total of 60.9%). As for the three dimensions of the urban form, the overall importance of the functional, mesoscale and human-scale morphological variables are 18.6%, 34.5%and 7.9% respectively.

Table 2. Relative Importance of Variables.

Variable	Relative Importance (%)	Rank	Sum (%)
Demographic and Socio-economic			0.316
urbanization rate	0.095	1	
housing price	0.071	3	
per capita GDP of the selected urban area	0.060	4	
population density	0.057	5	
per capita GDP of the city	0.020	17	
the proportion of GDP in the tertiary industry	0.013	26	
Meso-scale Morphological			0.345
street intersection density	0.086	2	
average block size	0.054	6	
building density	0.046	7	
street density	0.040	8	
floor area ratio	0.036	9	
walking accessibility	0.024	14	
riding accessibility	0.016	23	
vehicle accessibility	0.014	25	
street length	0.011	30	
Functional			0.186
functional density	0.035	10	
primary school accessibility	0.035	11	
bus stop accessibility	0.034	12	
kindergarten accessibility	0.020	18	
living facility availability	0.017	19	
functional diversity	0.015	27	
shopping facility availability	0.013	28	
catering facility availability	0.011	29	
leisure facility availability	0.006	37	
Human-scale Morphological			0.079
street facility visibility	0.020	16	
vegetation visibility	0.016	22	
enclosure degree	0.011	31	
motorization degree	0.009	32	
aspect ratio	0.008	34	
nearline rate	0.007	35	
pedestrian degree	0.007	36	
City classification	-	-	0.075
the average for all cities	0.007	37	

In particular, street intersection density, the most important urban form feature, has importance of 8.6%, followed by block size, building density, and street density. This is not surprising, as Jacobs pointed out that smaller blocks and denser streets are the basic conditions for vitality (Jacobs, 1961). The results also highlight the importance of street location. For instance, the importance of primary school and bus stop accessibility is higher, ranking 11 and 12 respectively. It is reasonable that these variables reflect whether the streets can attract community public activities.

A comparison between different urban form variables shows several interesting results. First, the relative importance of land development intensity was lower than that of the floor area ratio (FAR). Higher horizontal built-up coverage, by providing more ground spaces facing streets, can create greater opportunities for various street activities. In contrast, a higher degree of vertical building space concentration reduces the chances of pedestrian access (Gan et al., 2021). Second, the functional density is more than twice as important as the functional diversity, indicating that the number of functional facilities, rather than their functional entropy, plays a key role in attracting street use. In addition, The effects of the proportion of catering, living, and shopping facilities are relatively low (<1.5%). Only the visibility of street facilities is slightly more important in the dimension of human-scale characteristics. However, compared with other dimensions, the influence of the other human-scale variables almost can be ignored (< 1.0%).

Nonlinear effects of urban form variables

The PDPs shows the marginal effect of one feature on the dependent variables. To grasp more important dependency features, we used cubic spline interpolation to smooth the curves.

Figure 1 shows the impact of the mesoscale morphological variables on SAI. As shown, the increase in street intersection density can effectively improve the SAI within the range of 0–0.4. There is a negative correlation between street density and SAI, and there is a significant inflection point at 12.5 km/km².

Most related studies suggest that smaller blocks are more conducive to vitality, while our research refines this view by indicating that the negative effect of block scale is greater when less than 5ha. The relationship between building density and SAI is nearly linear. By contrast, when it exceeds 0.5, street vitality shows a downward trend. This yields new insights: a too high building density will inhibit street activities, which may be attributed to the fact that there are only a few shantytowns in the urban areas where the building density exceeds 0.5, and the poor space quality leads to a decline in vitality. When in the range of 0.5 to 2.0, the floor area ratio (FAR) presents a positive effect, followed by a negative impact when exceeding 2.0. This is reasonable because, at a low level of FAR, the block is generally open, for which a higher intensity of land use brings more street space use. However, when the FAR exceeds a certain level, residents usually have less access to the streets.

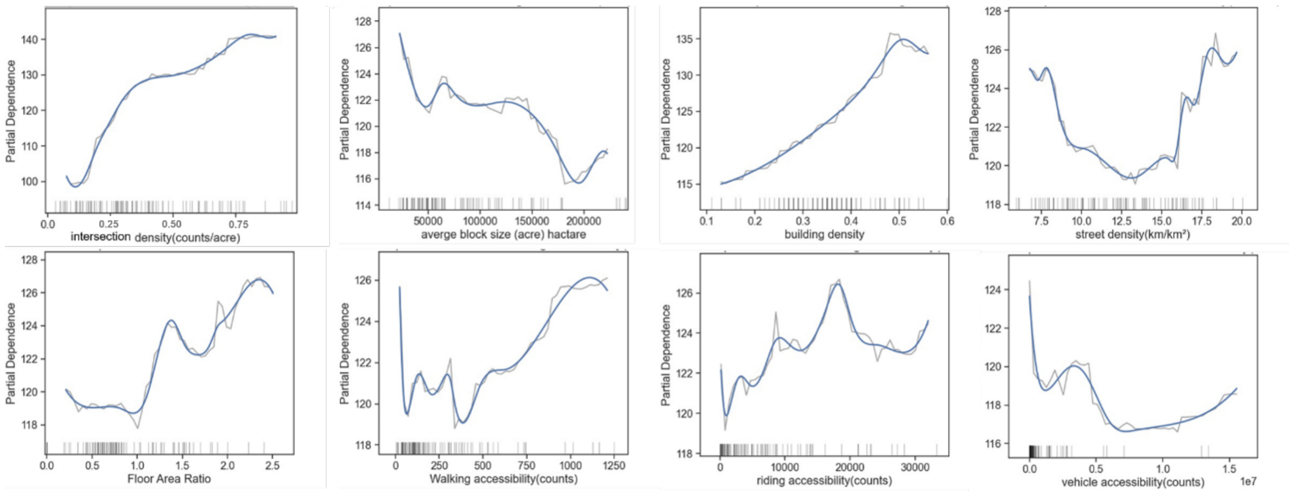

***Figure 1.** Threshold effects of mesoscale morphological urban form characteristics on SAI.*

The street network walking, riding and vehicle accessibility is measured by space syntax tools when the radius is set as 400m, 1200m and n respectively(Zhang and Chiaradia, 2019) and they all present a threshold effect. In general, walking accessibility has a positive effect on SAI when it reaches a certain level. Riding accessibility shows a positive effect at low values, but the marginal effect disappears when it exceeds a certain value, and car accessibility has a negative effect on the whole. This is consistent with the notion that community street activities are more closely related to short-distance walking or cycling activities than motor vehicle travel.

Figure 2 illustrates the impact of functional urban form characteristics on the SAI. The plot for function density shows that it has a positive association with SAI with a linear effect. In addition, based on the number of primary school facilities within the 500m buffer zone around the street, the positive impact of primary school accessibility appears when it is less than 10 and then tends to saturate. However, with the increasing bus accessibility, street vitality shows a tendency to decline first and then to rise, with the inflection point at approximately 10.

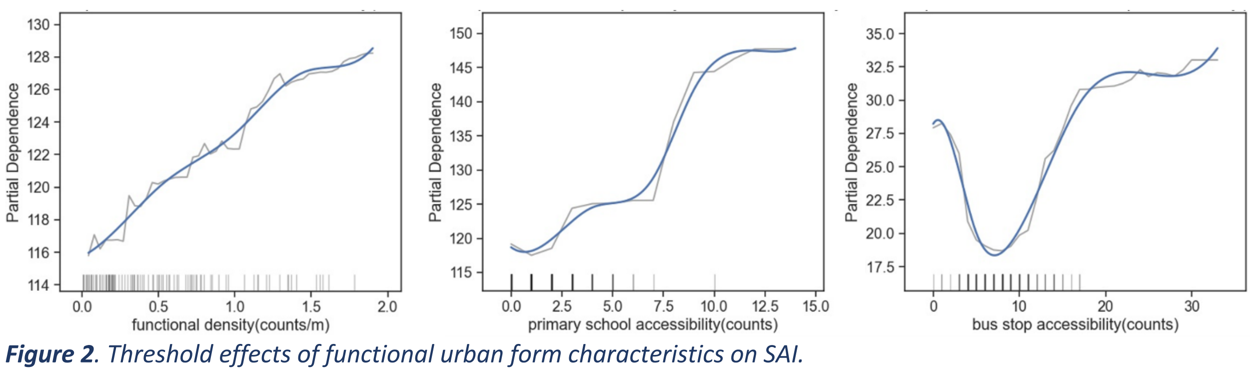

***Figure 2**. Threshold effects of functional urban form characteristics on SAI.*

When the kindergarten index exceeds 10, its marginal effect disappears. This can be understood through that regardless of the number of kindergartens, they will not attract more people beyond their service radius. The marginal effect of primary schools decreases after the value exceeds 8, and disappears after reaching 12. Bus stops are different from the former two. When the proximity is close to 18, the street vitality decreases sharply. Once this value is exceeded, the influence of the proximity of the bus facilities changes from negative to positive, which can be explained by the existence of transfer hubs when the bus facilities reach a low (5–10) or high (more than 20) level; thus, in areas like the centre of a residential group or urban area, it attracts more people.

The relative importance of human-scale morphological variables is low, but the obvious threshold effect on street vitality shown in Figure 3 is also worthy of attention. For example, the street facilities visibility in the streetscape is positively correlated with street vitality. When the street facilities' visibility exceeds 0.3, the marginal benefits increase. However, the vegetation is different, which shows a negative effect, and the data fluctuate greatly after 0.2, which may be attributed to noise in the data. When the degree of enclosure exceeds 0.85, its marginal benefit increases.

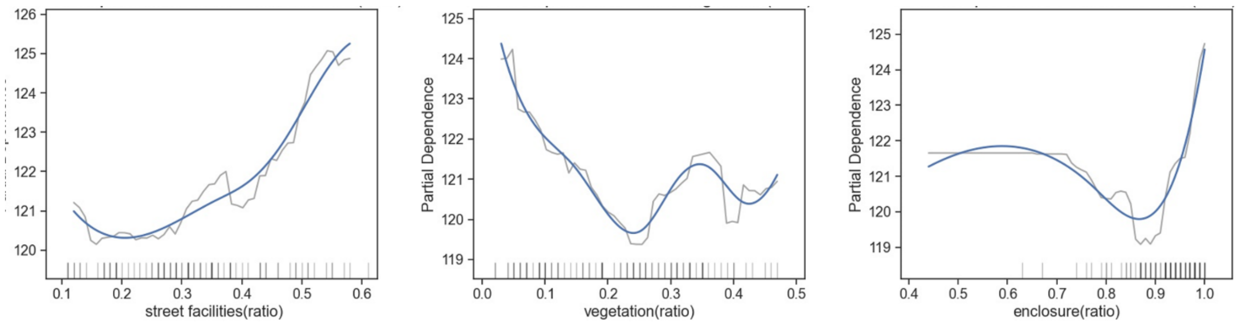

Figure 3. *Threshold effects of human-scale environmental characteristics on SAI.*

Conclusions

Using data from 12 old urban areas in China, this study examined the joint influences of the three dimensions of urban formal characteristics on SAI, controlling for demographics, economics, and other factors. The overall contribution to the literature is threefold. First, using large-scale data from different cities rather than a single city makes the analysis conclusion more generalisable. Second, this study considers both the top-down and human-scale urban form variables, which is rare in current research. Therefore, it can more comprehensively compare the effectiveness of each dimension of the environmental characteristic variables on street vitality. Third, the results show that the nonlinear effect of the urban form is widespread, which has been ignored in previous vitality-related research. Fourth, the threshold effect and effective influence range of each environmental indicator can be obtained through an analysis of the mechanism underlying the nonlinear influence, which is expected to provide the basis for the setting range of the spatial form index in design practice.

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