INTERPRETING GENDER DIFFERENTIATION IN URBAN CONSUMPTION PLACES BASED ON THE PREFERENCE LEVEL OF SPATIAL PERCEPTION

A Case Study of Four Commercial Areas in Beijing

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Abstract. Taking Street view map and Random forest model as the applications and four consumption places in Beijing as case studies, this study proposes a method that maps spatial perception preferences at the local scale to the global scale by following steps: Firstly, download street view images of consumption places from BaiduMap API, then combined the preference of the local street view images scores by the volunteers of both genders and the proportion of visual elements in the images, predicted the preference level of case areas at the global scale by the Random forest model, and finally, through FCN model and sDNA model, fully revealed the gender differentiation phenomenon of consumption places at the image, function and location contents. The results indicate that both genders have a preference for places of Catering function. Besides, females generally prefer consumption places with more conspicuous signboards, greening and better spatial design quality, and have clear pre-determined consumption targets; males generally prefer consumption places with more conspicuous columns, smaller signboards, and have less demand for the spatial design quality of consumption places.

Keywords. Random Forest Model,FCN Model, Built Environment, Consumption Places, SDNA Model

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1. Introduction

With the advancement of urbanisation and the improvement of the economic level, the development mode of Chinese cities has changed from traditional production-oriented to consumption-oriented (He and Lin, 2015). The spatial quality and urban distribution of consumption places can have a significant impact on residents' public activities. Through this view, extensive researches have been conducted on the spatial quality indicator of urban consumption places (Liu et al., 2020; Chen and Wang, 2009). However, the above studies are mainly limited to the planning and function level and lack the description of residents' subjective spatial perception preferences; in addition, these studies regard residents as a whole group, ignoring the influence of gender factors on consumption preferences. Therefore, it is necessary to explore a subjective perception-based measurement method to comprehensively describe the spatial preference patterns of residents' consumption behaviours and the gender differentiation phenomenon in consumption places.

Street view map and Random forest model provide a possibility to implement the above approach (Immitzer et al., 2012; Long, 2016). The former provides a vast amount of urban street view images, which can display the spatial scene images of urban areas; the latter can predict the scores of the full sample based on the scores of a test sample. With these tools, volunteers of both genders only need to score a small sample of street view images, and then the method can predict scores for the whole research area. Therefore, this paper will be unfolded from a local street view image study to a global spatial distribution study, and try to propose a quantitative evaluation method based on subjective spatial perception preference, then reveal the gender differentiation phenomenon of urban consumption places.

2. Methodology

2.1. RESEARCH FRAMEWORK

The research framework consists of four phases: In the first phase, the POIs (points of interest) of all consumption places in the study area are acquired, and the street view images of them are downloaded through the Street View Map API. In the second phase, the trained FCN (Fully Convolutional Networks) model is applied to conduct semantic segmentation of building facade elements in street view images to establish a quantitative measure of their visual characteristics. In the third phase, volunteers of both genders are invited to score the perceived preference level of sampled street view images, then the Random forest model is trained, and the scoring samples with higher accuracy are selected to predict the gender preference scores of all selected consumption places. In the fourth stage, we distinguish the gender preference points and analyse the gender differentiation phenomenon through their quantitative measurement.

2.2. STUDY AREAS AND DATA SOURCES

The study areas of this paper include four well-renowned commercial areas in Beijing: Dongsi, Xisi, Di'anmen and Qianmen (As shown in Figure 1). The reasons for selection are as follows: Firstly, the commercial spaces in these areas have been developed for a long period, and accurate POIs of consumption places can be comprehensively obtained. Secondly, these areas are located in Beijing's historic preservation area, and the buildings are mostly one-story courtyards, so the obtained street view images can directly exhibit the visual characteristics of the corresponding consumption places.

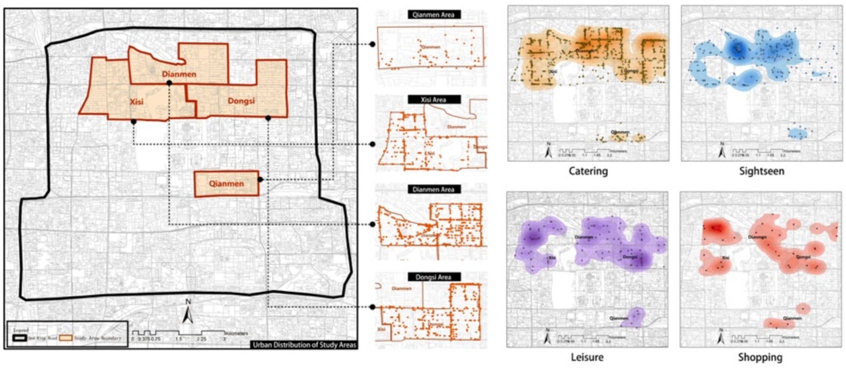

Figure 1. Distribution and kernel density of the study areas

According to the four phases in the research framework, the data to be acquired in this paper include the data on commercial district boundary and surrounding road network, the data on consumption places' POIs within the study area, and the data on street view images of POIs. The data sources are as follows: 1) Commercial district boundary and surrounding road network data obtained through the OSM website (2022). 2) Consumption places' POIs data obtained through the Peking University Geodata platform (2022). 3) Street view image data is downloaded through Baidu Street View Map (2022) (As Figure 2 shows). After the data acquisition, the first two types of data were performed in the Arcmap platform and were classified according to four functional categories of Leisure, Catering, Shopping and Sightseeing, with 14 subcategories (Table 1).

Table 1. Categories of the Functions of Selected POIs

Category	Subcategory	Number of POIs	Percentage of Dataset	
Leisure	Entertainment venue	54	2.89%	5.40%
	Beauty salon	25	1.34%	
	Massage parlour	10	0.53%	
	Performance center	12	0.64%	
Catering	Chinese formal dining	1095	58.56%	77.27%
	Bar&Pub	114	6.10%	
	Western formal dining	110	5.88%	
	Fast food restaurant	99	5.29%	
	Cafe&Tea	27	1.44%	

Shopping	Wholesale markets	6	0.32%	2.30%
	Supermarket	34	1.82%	
	Grocery store	3	0.16%	
Sightseeing	Scenic Area	270	14.44%	15.03%
	Park&square	11	0.59%	

Figure 2. Sample images of Baidu Street View Map

2.3. TOOLS

2.3.1. FCN MODEL

FCN model was selected to quantify the visual features of street view images (Figure 3). The model has a high image segmentation accuracy and can effectively identify various types of facade elements in street view images and reveal their proportions in the images (Huang et al., 2020). Prof. Q. Guan's team at the China University of Geosciences trained FCN with ADE_20K training dataset and obtained accurate segmentation accuracy (0.8144), which was packaged as an open-source software, through which the image semantic segmentation steps in this paper will be implemented (Yao et al., 2019).

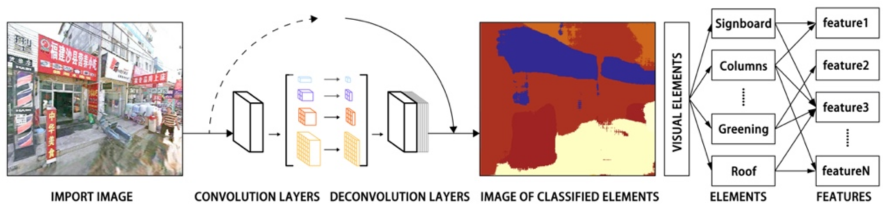

Figure 3. Mechanisms of image semantic segmentation by FCN

To accurately describe the visual characteristics of consumption places, the study selected roof (corresponding to the ceiling tag), column (corresponding to the column; pillar tag), signboard (corresponding to the signboard; sign tag), and greenery (corresponding to the plant; flora; plantlife, grass, flower tag) categories of visual elements, calculate the proportion of each category in the image, and divide them by the proportion of the building facade (corresponding to the building; edifice tag) in the image to describe the proportion of each element in the form of the facade, and then quantitatively measure the visual characteristics of the consumption place.

2.3.2. RANDOM FOREST MODEL

Random forest model is an unsupervised machine learning model which obtains local sample features by random sampling and performs predictive classification of the full domain scores (Breiman, 2001). Its application steps are: 1) draw a few samples from all samples with playback, 2) randomly select several features among all the features of the samples to score and playback, and build a decision tree between the features and the samples by multiple random sampling, 3) repeat the first and second steps several times to generate multiple decision trees, 4) add up the predictions for all the decision trees and assign predicted scores to all samples. The predicted value is calculated as in Eq. (1):

$$\mathrm{RF}(x) = \frac{1}{B}\sum_{i=1}^{B} T_{i,\,z_i}(x) \tag{1}$$

$\mathrm{RF}(x)$ in Eq. (1) is the predicted value of the Random forest, B denotes a total of B decision trees, z_i denotes the training set used for the i-th decision tree, which is the subset obtained from all training sets sampled by ranks and columns using the bagging method, and $T_{i,\,z_i}$ is the number of training rounds.

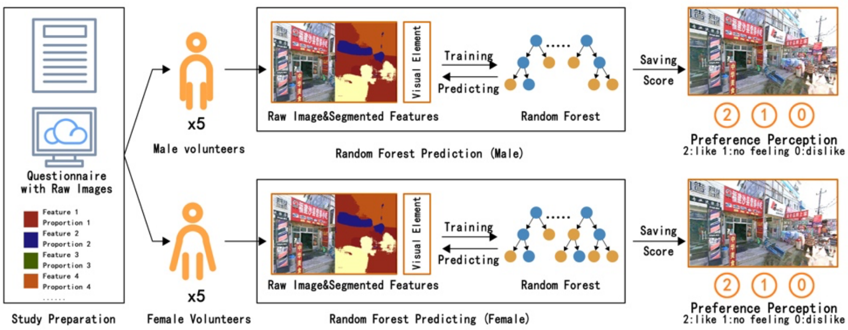

Figure 4. Mechanisms of Random forest model

As shown in Figure 4, 250 street view images were randomly sampled, and then ten male and ten female volunteers scored the sampled images according to the principle of '2-like, 1-no feeling, 0-dislike'. Finally, the training data set was constructed based on the proportion of the four types of visual elements and the scoring results. After the scoring stage, Random forest model was trained by the fit() method in Python, and the predict accuracy was calculated by the score() method. Then the samples with higher accuracy were selected to predict the preference levels of consumption places in the whole study area.

2.3.3. sDNA MODEL

sDNA (Spatial Design Network Analysis) is a spatial analysis tool developed by the Cardiff School of Planning & Geography and the Sustainable Places Research Institute

(SPRI). This tool can quantify the spatial attractiveness and accessibility attributes of a given segment Map. The location characteristic to be described in this study is the spatial attractiveness of male and female preference points in the road network system they are located in, so the NQPDA (Network Quantity Penalized for Distance, Angular) parameter is selected, which is calculated as shown in Eq. (2):

$$\mathrm{NQPDA} = \sum_{y \in R_x} \frac{P(y)}{d_\theta(x,y)} \tag{2}$$

In Eq. (2), $P(y)$ denotes the angle-based weight of a node y within the search radius R and $d_\theta(x, y)$ is the shortest topological distance from node x to node y. The larger the value of NQPDA, the stronger the spatial attractiveness of the selected point, and vice versa. In this study, since the mode of excursions in the study area is walking, a walking preference distance of 1500m for commercial activities was selected as the search radius to measure the NQPDA values for each gender preference point.

3. Experiment and result

3.1. IMAGE SEMANTIC SEGMENTATION RESULTS OF FCN MODEL

According to the research framework, a total of 6694 street view images of consumption places were obtained through the Baidu Street View Map API (each point obtained four images of 0°, 90°, 180° and 270°). Firstly, the FCN model is applied to conduct semantic segmentation of all acquired street view images, and then the segmentation data from four angles are summed up to count the proportion of four types of visual elements in the building facade to quantify and measure their visual characteristics. The percentages of the four types of visual elements in all points are shown in Table 2.

Table 2. Proportion of selected elements on the building façade

	Signboard	Greening	Roof	Columns
Proportion	14.75%	18.16%	11.32%	11.48%

3.2. PREDICTION RESULTS OF RANDOM FOREST MODEL

According to the research framework, 250 street view images were taken, and ten volunteers of each gender scored the preference level in the form of an online questionnaire. Then the samples were input into Random forest model to calculate their predict accuracy. The results are shown in Figure 5.

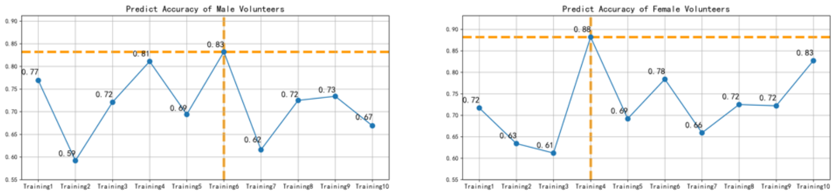

Figure 5. Predict accuracy of Random forest model training

In terms of gender, the predict accuracy of the 6th male training sample peaked as high as 0.83, so the regression results of this sample are taken to predict the male preference levels of all consumption places. The predict accuracy of the 4th female training sample peaked as high as 0.88, and the regression results of this sample are taken to predict the female preference levels of all consumption places.

3.3. ANALYSIS BASED ON FCN AND RANDOM FOREST MODEL

3.3.1. GENDER DIFFERENTIATION AT IMAGE CONTENT

Based on the segmentation and the prediction results of the full domain preference situation, the consumption places are grouped according to the preference level, and the proportion of different visual elements in the building façade is counted by gender. The results are shown in Figure 6 and Table 3.

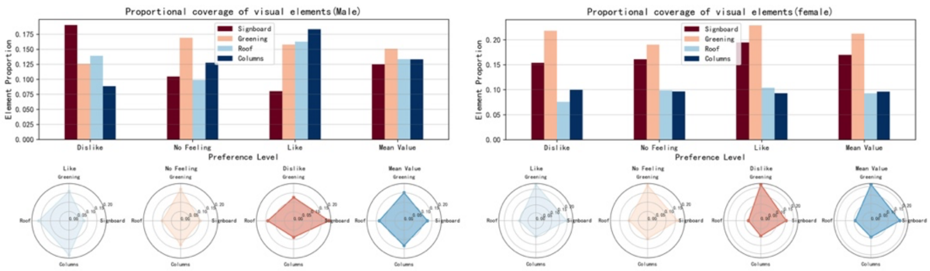

Figure 6. Proportion of visual elements in the building facade

Table 3. Proportional of visual elements of each preference levels

Preference Level	Signboard	Greening	Roof	Columns
Male				
Dislike	15.41%	21.79%	7.56%	9.27%
No Feeling	16.11%	18.99%	9.88%	9.68%
Like	19.47%	22.89%	10.42%	9.97%
Mean Value	17.00%	21.22%	9.29%	9.64%
Female				
Preference Level	Signboard	Greening	Roof	Columns
Dislike	19.04%	12.59%	13.92%	8.86%
No Feeling	10.47%	16.93%	9.88%	12.78%
Like	8.03%	15.78%	16.29%	18.33%
Mean Value	12.51%	15.10%	13.36%	13.32%

The radar chart distributions of females' predicted results are relatively consistent at different levels of preference, with the greening element accounting for the most (mean value of 21.22%), followed by the signboard element (mean value of 17.00%) and roof and columns element always accounting for a smaller proportion (mean values of 9.29% and 9.64% respectively), indicating that the first two elements generate the main attraction in the females' consumption. In addition, the increasing trend of the signboard element preference level indicates that the greater the proportion of this element in the facade, the more likely it attracts females. In contrast, there was a significant difference in the proportion of visual elements at different preference levels for male predicted results, with the proportion of signboard element decreasing significantly (19.04% to 8.03%) and the proportion of columns element increasing significantly (8.86% to 18.33%) as the preference level increased. While the percentages of the other two elements did not show a significant pattern of change, their attractiveness to men declined as the proportion of the signboard element increased.

3.3.2. GENDER DIFFERENTIATION AT FUNCTION CONTENT

Based on the results of the full domain prediction for both genders, the mean value of the preference level was counted in all points by function (the results are shown in Figure 7). When the mean value is greater than 1, the corresponding function category is preferred, and vice versa, not preferred.

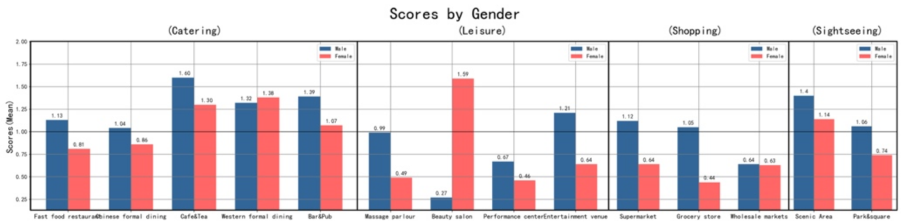

Figure 7. Mean values of the preference levels of all points

According to the results, the mean scores of the Catering are higher than those of the Leisure, while those of Shopping and Sightseeing are lower, and the mean preference scores of males are higher than those of females. In terms of detailed categories, males' preference scores in the Catering are higher than 1, especially in the two subcategories of Cafe&Tea and Bar&Pub, which favour the conversation atmosphere, with mean scores as high as 1.60 and 1.39, while females are not interested in Fast food and Chinese formal dining, and are more interested in Western formal dining and Cafe&Tea, which have better spatial design quality and are more popular, with scores fluctuating around 1.35. In terms of Leisure, males only preferred Entertainment venue (mean score of 1.21), while females preferred Beauty salon (mean score of 1.59). In terms of Sightseeing, females only preferred the Scenic area, while males preferred both subcategories.

Since the study areas are located in the Hutongs of the old city of Beijing, there are no modern shopping malls or shopping districts, and the spatial design quality of other shopping places is poor, so the preference scores of females for Shopping are low (less than 0.65), while males have lower requirements for spatial quality and prefer Supermarket and Grocery store which are close to their daily life (value greater than one).

3.3.3. GENDER DIFFERENTIATION AT LOCATION CONTENT

The POIs with the gender preference (score of 2) were labelled in the Arcmap platform, and then the NQPDA values were also calculated. The spatial distribution of the gender preference points was marked on the map by kernel density, and the distribution of NQPDA values was presented in the form of a box plot. The results are shown in Figure 8.

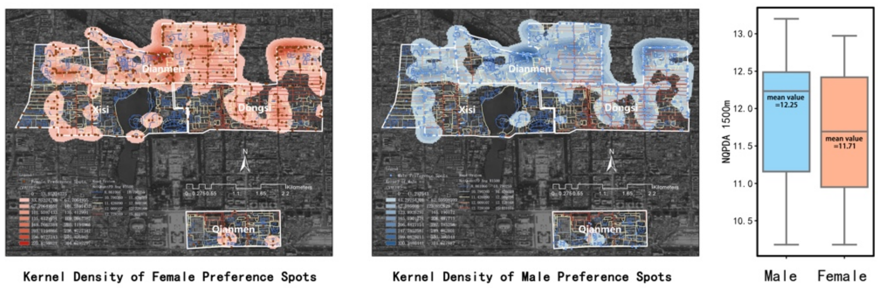

Figure 8. Kernel density of sites by gender preference

The mean value of male preference points is significantly higher than females (12.25 and 11.73). Compared with the kernel density map, the consumption range of both genders is more consistent at the macro level, with a higher density in the Di'anmen area and a lower density in the Qianmen area, where both Xisi and Dongsi are distributed along the main traffic axes in the region. However, microscopically, male preference points are concentrated in roads with higher NQPDA, indicating that their consumption behaviour is mainly guided by the spatial attractiveness of consumption places without a strong pre-determined purpose, while female preference points show a more uniform distribution, indicating that their consumption behaviour has a strong pre-determined purpose and does not comply with the spatial attractiveness.

4. Conclusion

Through the FCN, Random forest and sDNA models, this paper analyses the gender differentiation phenomenon of consumption places by taking four commercial areas of Beijing as examples. The results indicate significant gender differences in the three contents: both genders prefer Catering consumption. Females generally prefer to choose places with more conspicuous signboards, better greening, and better spatial design quality and have a pre-determined purpose of consumption, with less demand for the spatial attractiveness of consumption places. Males generally prefer to choose places with more conspicuous columns, smaller signboards, and more robust spatial attractiveness, with less demand for spatial design quality. Males prefer daily and communication places, and females prefer high-quality exquisite spaces.

Generally, this study proposes a subjective perceived preference regression model based on street view images that can accurately, efficiently, and quantitatively evaluate residents' preferences for consumption places at the urban scale, and guide the optimisation of gender equity in old commercial areas. It has a high measurement efficiency and broader application scope. However, this study is still limited in that the selected cases are all old commercial areas in the main city of Beijing, lacking attention to other urban areas of the city, and lacking detailed optimisation strategies. This is also a focus for future research.

References

Baidu Street View Map. (2022). Street View Images. Retrieved November 5, 2022, from https://quanjing.baidu.com/

Breiman, L. (2001). Random Forests. Machine Learning, 45(1), 5-32.

Chen, Y. H., & Wang, Y. Q. (2009). Approach to the Development of Traditional Urban Commercial Area:A Case Study of Xiamen. Arid Land Geography, 32(1), 152-158.

He, S. J., & Lin, G. C. S. (2015). Producing and Consuming China's New Urban Space: State, Market and Society. Urban Studies, 52(15), 2757-2773. https://doi.org/10.1177/0042098015604810

Huang, H. S., Lan, Y. B., Yang, A. Q., Zhang, Y. L., Wen, S., & Deng, J. Z. (2020). Deep Learning Versus Object-based Image Analysis (OBIA) in Weed Mapping of UAV Imagery. International Journal OF Remote Sensing, 41(9), 3446-3479. https://doi.org/10.1080/01431161.2019.1706112

Immitzer, M., Atzberger, C., & Koukal, T. (2012). Tree Species Classification with Random Forest Using Very High Spatial Resolution 8-Band WorldView-2 Satellite Data. Remote Sensing, 4(9), 2661-2693. https://doi.org/10.3390/rs4092661

Liu, Y., Yang, L. C., & Chau, K. W. (2020). Impacts of Tourism Demand on Retail Property Prices in a Shopping Destination. Sustainability, 12(4). https://doi.org/10.3390/su12041361

Long, Y. (2016). Redefining Chinese City System with Emerging New Data. Applied Geography, 75, 36-48. https://doi.org/10.1016/j.apgeog.2016.08.002

OSM website. (2022). Commercial District Boundary and Surrounding Road Networks. Retrieved November 5, 2022, from https://www.openstreetmap.org/

Peking University Geodata platform. (2022). Consumption Places POIs. Retrieved November 5, 2022, from https://geodata.pku.edu.cn

Yao, Y., Liang, Z. T., Yuan, Z. H., Liu, P. H., Bie, Y. P., Zhang, J. B., . . . Guan, Q. F. (2019). A Human-machine Adversarial Scoring Framework for Urban Perception Assessment Using Street-View Images. International Journal of Geographical Information Science, 33(12), 2363-2384. https://doi.org/10.1080/13658816.2019.1643024