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Perceptions of built environment and health outcomes for older Chinese in Beijing: A big data approach with street view images and deep learning technique

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ABSTRACT

Built environment attributes have been demonstrated to be associated with various health outcomes. However, most empirical studies have typically focused on objective built environmental measures. Still, perceptions of the built environment also play an important role in health and may complement studies with objective measures. Some built environment attributes, such as liveliness or beauty, are difficult to measure objectively. Traditional methods to assess perceptions of the built environment, such as questionnaires and focus groups, are time-consuming and prone to recall bias. The recent development in machine deep learning techniques and big data of street view images, makes it possible to assess perceptions of the built environment with street view images for a large-scale study area. By using online free Tencent Street View (TSV) images, this study assessed six perceptual attributes of the built environment: wealth, safety, liveliness, depression, bore and beauty. These attributes were associated with both the physical and the mental health outcomes of 1231 older adults in 48 neighborhoods in the Haidian District, Beijing, China. Results show that perceived safety was significantly associated with both the physical and mental health outcomes. Perceived depression and beauty were significant related to older adults' mental health, while perceived wealth, bore and liveliness were significantly related to their physical health. The findings carry important policy implications and hence contribute to the development of healthy cities. It is urgent to improve residents' positive perceptions and decrease their negative perceptions of the built environment, especially in neighborhoods that are highly populated by older adults.

1. Introduction

With the rapid process of urbanization, more than one billion people will live in Chinese cities in by 2030 (Development Research Center of the State Council, 2014). However, due to high population density, heavy air pollution, and lack of public facilities, urban agglomerations will face various health problems, including physical and mental diseases. In this respect, tackling urban residents' health problems has become a global challenge for future cities (Gong et al., 2012; Grekousis & Liu, 2019). The urban environment, especially the neighborhood environment, plays an important role in affecting urban residents' health because residents spend most of their time in their residential neighborhoods, compared to the places of work and entertainment (Helbich, 2018; Pearce, Shortt, Rind, & Mitchell, 2016). In recent years, perceptions of the built environment have attracted research attention because subjective urban environment attributes are more likely to directly affect residents' perceptions and health-related behaviors, compared to objective physical environment attributes (Zhang et al., 2018). Studies of subjective urban environment attributes can further inform and complement studies of environment-health outcomes association (Salesses, Schechtner, & Hidalgo, 2013; Zhang et al., 2018).

Health problems of the older adults have also recently attracted more research attention because the aging population is becoming a global issue, and some countries, especially developing countries, are

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not well-prepared to tackle this issue (Prince et al., 2015). Older adults are more likely to suffer from health problems in China because of their low socioeconomic status and degeneration of body functions (Li & Zhang, 2013; Sun, Lucas, Meng, & Zhang, 2011). Compared with young adults, older adults may be more influenced by their neighborhood environment due to their lower mobility (Wiles, Leibing, Guberman, Reeve, & Allen, 2012). Thus, identifying the relationship between perceptions of the neighborhood environment and urban older residents' health outcomes has become a public health priority and may have important policy implications for China in the near future (Gao, Ahern, & Koshland, 2016; Liu, Dijst, Faber, Geertman, & Cui, 2017).

1.1. Urban perception and health outcomes

Previous studies have generally supported the idea that residents' perception of the built environment influence their well-being and health outcomes (Dong, Wolf, Alexiou, & Arribas-Bel, 2019; Grahn & Stigsdotter, 2010; Özgüner, Eraslan, & Yilmaz, 2012; Parsons, 1991; Rollero & De Piccoli, 2010; Thompson, 2011; Zhang, Chen, Sun, & Bao, 2013). Both direct and indirect effects of the built environment perception on health outcomes should be noted (Özgüner et al., 2012; Parsons, 1991). First, according to stress reduction theory (SRT) (Ulrich et al., 1991) and attention restoration theory (ART) (Kaplan, 1995), people's perception of the environment may directly influence mental stress, which is important for their overall health. SRT indicates that a positive perception of the environment may arise from “evolutionary adaptation” and “biological adaptation”. For instance, because early humans could always access food resources and hide themselves in a certain environment, such as green spaces, they might have developed a positive perception of such an environment (Ulrich et al., 1991). ART indicates that a positive perception of the environment may provide a buffer between daily stressors and people's mental stress (Kaplan, 1995).

Second, people's perception of the environment may indirectly influence health through health-related behaviors (Mehrabian & Russell, 1974) such as physical activities and social contacts, which are important for their health (Duncan, Mummery, Steele, Caperchione, & Schofield, 2009; Middlestadt, Anderson, & Ramos, 2015; Nogueira et al., 2013; van Deurzen et al., 2016; Weimann et al., 2017). The Arabian-Russell Model theory (AR model) indicates that people's perception of the environment may influence their emotions, and then their emotion may affect their behavioral choices (Mehrabian & Russell, 1974). For example, when people have a positive perception of a certain environment, they are more likely to stay and participate in activities in that environment (Mehrabian & Russell, 1974). Therefore, positive perceptions of a neighborhood environment can increase residents' propensity to participate in physical activities, as well as interact with social contacts and others (Duncan et al., 2009; Middlestadt et al., 2015; Nogueira et al., 2013; van Deurzen et al., 2016; Weimann et al., 2017).

1.2. Methods to assess the perception of the built environment

Assessing the perception of the built environment in epidemiological studies is not trivial; multiple techniques are conceivable (Grahn & Stigsdotter, 2010; Özgüner et al., 2012; Parsons, 1991; Rollero & De Piccoli, 2010; Thompson, 2011; Zhang et al., 2013). Questionnaires, the most typical method to assess perceptions of the built environment, often utilize a Likert or a numeric rating scale (e.g., assessing safety based on a 1–5 rating scale) (Grahn & Stigsdotter, 2010; Parsons, 1991; Rollero & De Piccoli, 2010; Zhang et al., 2013), or open-ended questions to assess respondents' evaluations of the research area (e.g., “How do you feel about and perceive the research area?”) (Özgüner et al., 2012; Thompson, 2011). Substantial methodological drawbacks of questionnaires are that they are time-consuming, labor-intensive and have a small sample size (Salesses et al., 2013; Zhang et al., 2018). First, to collect sufficient questionnaires, researchers must find a large number of respondents, which may be a long-term process (Salesses et al., 2013; Zhang et al., 2018). Second, during the process of collecting the questionnaires, many researchers must be involved in the collection process and subsequently clean and summarize the data, which can be tedious and prone to errors (Salesses et al., 2013; Zhang et al., 2018). Finally, since collecting questionnaires is time-consuming and labor-intensive, it is impossible to collect data for many participants or study areas (Salesses et al., 2013; Zhang et al., 2018).

In recent years, with the development of computer vision and deep learning technology, it is feasible to identify the semantic information such as sky (Li & Ratti, 2018a, 2018b; Wang et al., 2019), treepedia (Li, Ratti, & Seiferling, 2018) and green view index (Li, Zhang, Li, Kuzovkina, & Weiner, 2015, Li et al., 2015, Li, Zhang, Li, & Kuzovkina, 2016; Lu, 2018; Helbich et al., 2019) contained in streetscape images (Yan, Zhang, Wang, Paris, & Yu, 2016). Simultaneously, street view image services (e.g., Google, Tencent, and Baidu) provide big data of geo-tagged streetscape images, allowing users and researchers to virtually navigate through urban streets in many global cities (He, Páez, & Liu, 2017; Liu et al., 2015; Rundle, Bader, Richards, Neckerman, & Teitler, 2011; Zhang et al., 2017). Street view images can be collected for a large scale in a short time and they contain plenty of information for ground objects, so they have great potential for urban studies (Dubey, Naik, Parikh, Raskar, & Hidalgo, 2016; Salesses et al., 2013; Wang et al., 2019; Yao et al., 2019; Zhang et al., 2018). Hence, residents' urban perception is mainly based on street view ground objects (e.g., different elements, such as sky, greenery, buildings), so with a human-machine confrontation scoring process (by using scored street view images and deep learning technology, computers can weight street view ground objects automatically) computer can assess urban perception scores for each images in a large scale (Deza & Parikh, 2015; Dubey et al., 2016;Salesses et al., 2013; Zhang et al., 2018). Therefore, an innovative way to assess perceptions of the built environment is to use the deep learning technique in conjunction with street view image services. While these street view image services are a valuable source of place-based information about neighborhoods (He et al., 2017; Rzotkiewicz, Pearson, Dougherty, Shortridge, & Wilson, 2018; Zhang et al., 2017), the manual analyses of many pictures and larger areas is tedious. Zhang et al. (2018) used a convolutional neural network to semantically segment street view pictures into different elements, from which human perceptions were derived using SVM (support vector machine). Salesses et al. (2013) focused on the perception of safety using Google Street View and mapping its distribution across different cities. Quercia, O'Hare, and Cramer (2014) used crowd-sourcing ratings on streetscape images of 0.7 million streets to evaluate perceptions of safety and beauty. Deza and Parikh (2015) mainly focused on the perception of virality and liveliness of streetscape images. Dubey et al. (2016) concluded that the method of assessing perceptions of the built environment using street view image mainly focused on and performed well for six indicators: wealth, liveliness, safety, depression, bore and beauty.

1.3. The gaps

As shown in several reviews, previous studies often used questionnaire data to assess human perceptions of the built environment, which is time-consuming, labor-intensive, associated with a small sample size and only small-scale study areas. A recent review suggested that deep learning method blooming in computer science and can be well applied in urban environment researches (Grekousis, 2019; Grekousis & Liu, 2019). To overcome these constraints, the human-machine confrontation scoring method was recently developed (Salesses et al., 2013; Zhang et al., 2018). This method can effectively and accurately rate perceptions for a large number of streetscape images with human ratings for a subset of training images. However, for human-machine confrontation scoring method, the first step is to created dataset which is scored by human volunteers. Previous studies mainly used the online dataset which is score by online users (without users from mainland China). Urban perception may be influenced by residents' social and cultural background, so previous online dataset which is mainly scored by foreign users and collected in developed countries may not actually reflect urban perception in China. Thus, in this study we also try to assess urban perception based on dataset scored by Chinese residents. To our knowledge, this work is one among very few that have integrated CNNs in the machine confrontation scoring method based on images dataset scored by Chinese local residents, and the only one that specifically focuses on identifying linkages between human health and perceptions of the built environment. Therefore, the aim of this study is to assess perceptions of built environment for a large study areas with the human-machine confrontation scoring method (which mainly depends on deep learning AI method) and to analyze the associations between six perceptual attributes (i.e., perception of wealth, liveliness, safety, depression, bore and beauty) and health outcomes among older adults people in Beijing, China. The following research question is devised:

*Are both physical and mental health affected by urban perceptual indicators (*i.e., *perceptions of wealth, liveliness, safety, depression, bore and beauty) among the older adults in Beijing?*

The following two hypotheses are generated: a) perceived built environment attributes are correlated with health outcomes among the older adults, and b) physical and mental health are affected by different attributes. This study contributes to the literature in studying built environment perception-health outcomes using the human-machine interactive scoring method for a large number of streetscape images classified through deep learning convolutional neural network. It focuses on the older adults in Beijing – an understudied but vulnerable population group in a large Asian metropolis.

2. Methods

2.1. Study areas

The current study used data collected by a research team in Renmin University of China through the survey called Mental health survey of the older adults in Beijing conducted between March and August 2011. This survey was conducted in Haidian District in Beijing, because Haidian District is an ideal place to undertake field studies on older adults's depression. By December 2011, there were approximately 386,000 people over 60 years of age in Haidian District in Beijing, accounting for 22.2% of the total population. From 2011 to 2015, the number of older adults people in Haidian District had increased by approximately 20,000 per year, and the number of older adults people in Haidian District had reached approximately 470,000 in 2015 according to the Beijing Census. The researchers selected survey respondents through two stages. First, 48 residential neighborhoods were selected from 13 districts, using a stratified sampling method. Second, 30 persons from each sampled neighborhood were selected, also using a stratified sampling method. The final dataset included 1231 valid respondents after excluding respondents with missing health outcomes (the total number of respondents was 1350).

2.2. Accessing perceptions of the built environment using Tencent street view images and the deep learning method

The images were extracted from Tencent Map [https://map.qq.com/] which is the most comprehensive service with the largest image coverage providing street view photos. In total, 134,778 street view images were obtained for research areas in 2012. Our training dataset was based on nearly five million street view photos of major Chinese cities (Beijing, Shenzhen, Guangzhou, Shanghai, Wuhan and Hangzhou, etc.), our collected street view image database covers nearly all types of street sceneries in Chinese cities.

A machine learning approach was implemented to estimate urban perceptions from street view images. To circumvent the limitations of pixelwise classifications using an image's additive colors (i.e., red, green, and blue channels), we applied a semantic segmentation technique that is capable of accurately identifying elements from street view images (Yao et al., 2019; Zhang et al., 2018).

As deep learning performed well for pattern recognition tasks (LeCun, Bengio, & Hinton, 2015), we used a fully convolutional neural network for semantic segmentation (i.e., the FCN-8s) (Long, Shelhamer, & Darrell, 2015) to segment the street view images into 150 types of common elements (e.g., river, tree). The network architecture of a fully convolutional network contains only convolution and deconvolution layers for spatial convolution operations (Long et al., 2015). By using convolutional kernels to broaden the receptive fields of pixels, information about adjacent pixels was incorporated, thus enhancing the segmentation accuracy (Kang & Wang, 2014).

Fig. 1 summarizes the workflow of the street view image segmentation. To train the network, we used a collection of annotated images from the ADE20K scene parsing and segmentation database (Zhou et al., 2016, 2017). Details for the ANN architecture are presented in Table S1. ADE20K consists of a large number of annotated object categories (e.g., tree, car). Fig. 2 summarizes the workflow of assessing the perception of street view images. After obtaining the image segmentations by feeding the street view images into the trained model, a human-machine confrontation scoring system was employed to measure six attributes, including wealthy, safety, lively, beauty, boring and depressing following previous studies (Dubey et al., 2016; Zhang et al., 2018). The reason why we chose these six perceptual indicators only is that, as suggested by previous studies (Dubey et al., 2016; Zhang et al., 2018), they were representative of people's urban perception (including both positive and negative aspects of perception). Since people's urban perception is influenced by ground objects, so semantic objects can help us explain the features of urban perception more logically. Perception to the neighborhood built environment refers to human perceptions and individual's feelings about the environment where they live (Zhang et al., 2018). For example, safety score measures residents' sense of safety when living in the neighborhood. Thus, when assessing sense of safety based on street view image a person must assume that if he or she is living in such an environment, how safe he or she may feel. Specifically, 30 volunteers with balanced gender and age ratios (mean age = 35.68 years) were asked to score (0–10 points) the street view images (100 street view images for each volunteer) on these six attributes. After the volunteers rated a certain number (100 street view images for each volunteer) of street view images, a random forest model (Breiman, 2001) for automatic rating was trained by fitting the inputted rating scores with the proportion of 151 elements in the image segmentations. The model automatically recommended a rating score for a new image and referred it to the volunteers, who subsequently corrected the recommended score as well as calibrated the automatic scoring system. The calibrating process stopped when the recommended scores and volunteers' scores reached a high agreement (when the root-mean-square error score between the recommended scores and volunteers' scores was below 5 for at least 100 of the most recent images). We use a standardized way of reporting CNN architecture, hyperparameters and results as suggested by Grekousis (2019) for geographical studies utilizing artificial neural networks (see Appendix Table S1).

The automated scoring system was further validated with volunteers' scores for 100 images. One hundred Tencent view images were randomly selected, and perceptions of those images were again assessed by five volunteers. The scores from the automated scoring system were highly correlated with volunteers' scores in six perceptual indicators: wealthy (Pearson correlation coefficient $r = 0.98$, $p < .01$), safe scores ($r = 0.98$, $p < .05$), Lively ($r = 0.97$, $p < .05$), beautiful ($r = 0.96$, $p < .05$), Boring ($r = 0.96$, $p < .05$) and depressing ($r = 0.98$,

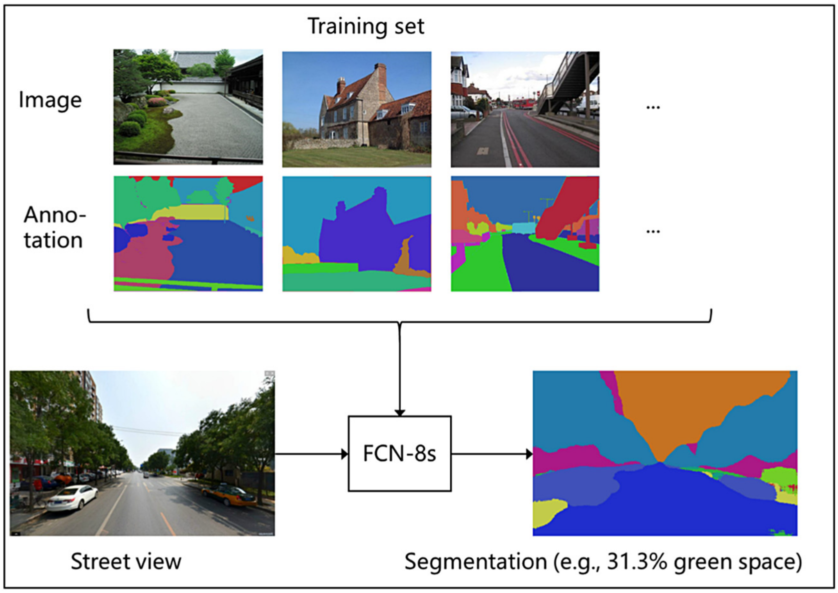

Fig. 1. Street view image segmentation through the convolutional neural network (FCN-8s).

$p < .05$).

In this way, we collected scores for six perceptual indicators by human-machine confrontation scoring. Thus, the measurement of each kind of streetscape perceptions per sampling point was represented by the average of that kind of perception scores over the four cardinal directions (0, 90, 180 and 270 degree). For each residential neighborhood, we calculated the mean streetscape perceptions per sampling point of six perceptual indicators within 1 km buffer.

2.3. Health outcomes variables

2.3.1. Mental health indicators

The mental health indicators were depression and anxiety, which were assessed using the Geriatric Depression Scale (GDS) (de Craen, Heeren, & Gussekloo, 2003) and Geriatric Anxiety Inventory (GAI) (Pachana et al., 2007). The GDS includes 15 questions that measure the mental state of residents over the previous week (i.e., feeling upset, feeling helpless, and feeling useless), while the GAI includes 20 questions that measure the mental condition of residents over the previous week (i.e., feeling scared, feeling nervous, and feeling worried). The average score for all items in the GDS and GAI was used to measure depression and anxiety, respectively.

2.3.2. Physical health indicators

The physical health indicators were the self-rated health condition (SRH) and chronic diseases. SRH was measured by responses to the following question: 'How would you describe your general physical health condition?' following previous studies (Kawachi, Kennedy, & Glass, 1999; Pei & Rodriguez, 2006). The five possible responses were transformed into a dichotomous indicator, where 1 = poor or very poor ('poor health') and 0 = fair, good, or very good ('good health'). In contrast, chronic diseases in this study were measured by self-reported

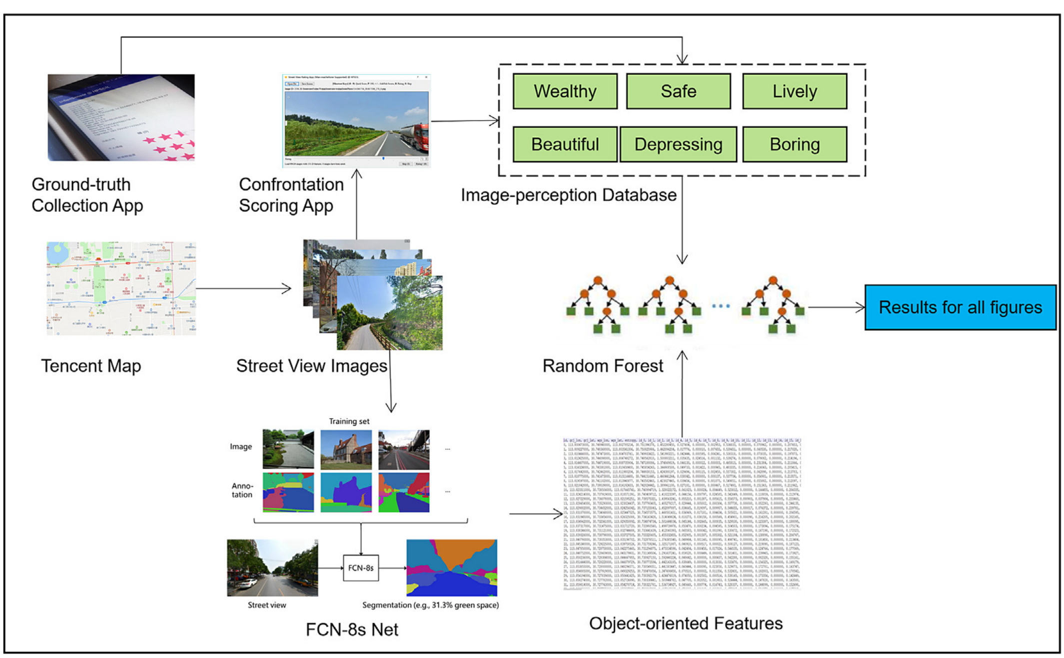

Fig. 2. Workflow for assessing street-level urban perceptions.

Table 1
Descriptive statistics for the variables.

Variables	Proportion/Mean (SD)
Dependent variables	
GDS Score	3.37 (2.73)
GAI Score	2.26 (4.26)
Chronic diseases	2.31 (2.10)
Self-rated health (%)	
Poor and very poor	11.54
General, good and very good	88.46
Independent variables	
Perceptions of built environment	
Wealthy	4.76 (6.81)
Safe	4.22 (5.50)
Lively	4.64 (7.83)
Depressing	5.61 (3.80)
Boring	6.14 (2.01)
Beautiful	4.08 (2.44)
Individual control variables	
Gender (%)	
Male	41.29
Female	58.71
Age	70.71 (7.03)
Education (%)	
Primary school or below	31.19
High school	43.95
College and above	24.86
Race (%)	
Chinese Han	96.34
Minority	3.66
Marital status (%)	
Single, divorced, and widowed	22.33
Married and living with spouse	76.68
Married but living apart from spouse	0.98
Hukou status (%)	
Local hukou	93.98
Nonlocal hukou	6.02
Functional ability (%)	
Limited	54.02
Not limited	45.98
Neighborhood control variables	
Population density (person/km^2)	7333.574 (2913.152)
Land use mix	0.443 (0.285)
Intersection density (number of intersections/km^2)	107.364 (30.010)

diagnosis of chronic diseases via the question: “Has a doctor ever told you that you suffer from the following diseases?” The chronic diseases included high blood pressure, diabetes, stroke and 22 other kinds of chronic diseases. We treated chronic diseases as a count variable since they followed a Poisson distribution.

2.4. Covariates

2.4.1. Individual covariates

We controlled for a series of individual-level variables, including gender (dichotomous variable: male = 1, female = 0), age (continuous variable in years), educational attainment (categorical variables: primary school = 0, high school = 1, college and above = 1), race (categorical variables: minority = 1, Han Chinese = 0), marital status (categorical variables: single = 0, married living with spouse = 1, married not living with spouse = 1) and hukou status (dichotomous variable: non-local hukou = 0, local hukou = 1), which is an official identification for local residents. Functional ability (categorized into restricted or not restricted using the 13-item Activities of Daily Living questionnaire (ADL) is a reliable measure of functional ability across different countries (Pluijm et al., 2005)). Table 1 shows the summary statistics for each variable.

2.4.2. Neighborhood covariates

Following Frank et al. (2006) we chose three land use-related variables including population density (continuous variable in person/km^2), street intersection density (continuous variable in number of intersections/km^2) and land use mix (continuous variable which ranges from 0 to 1).

2.5. Data analysis

We used multilevel regression models to estimate the associations between perceptions of the neighborhood environment and health outcomes (Raudenbush & Bryk, 2002). Such models were necessary due to the hierarchical structure of the data in which people were nested in neighborhoods. Specifically, the multilevel models were created according to the following steps. 1) Measurements of variance inflation factors (VIF = 5.804) were used to investigate multicollinearity among the variables. 2) We fitted the main models (Model 1–4) to identify the effect of the street view urban perception on respondents' health outcomes. We used metilevel liner regression for model 1 and 2, metilevel logit regression for model 3 and mutilevel poisson regression for model 4, since GDS and GAI scores were continuous variables, SRH was binary variable and chronic disease was counting variable. 3) We ran several models including setting the radius of the buffer as 2000 m, excluding respondents aged 85 years and above, excluding respondents who had problems with traversing 3–4 miles on foot or going up and down stairs unaided (Model 5–7) to test whether the results from Models 1–4 were robust.

3. Results

3.1. Study population characteristics

Table 1 shows the main characteristics of the study population. Briefly, respondents' mean GDS scores were 3.376 and mean GAI scores 2.264. On average, each respondents had 2 kinds of chronic diseases, and 12% respondents reported being unhealthy (poor and very poor health) while 88% respondents reported being healthy (generally good and very good health). With a higher proportion of females (59.709%), respondents' mean age was 70.714 years. Additionally, 31.191% of respondents had a primary school or lower educational attainment, 43.951% a high school education, and 24.858% a college or higher level education. Few respondents were minorities (3.660%) or married but living apart from their spouse (0.979%). A high proportion of respondents were not party members (55.870%) or had local hukou (93.984%). Few respondents were not functionally restricted (45.977%). The average population density in our study area was 7333.574 (person/km$^{2)}$, intersection density was 107.364 (number of intersections/km^2 and the score of mand use mix was 0.443). The objectives of the present study were to evaluate the potential associations between health outcomes and neighborhood street urban perception. The mean value of the wealthy score across 48 neighborhood was 4.765, the safe score was 4.221, the lively score was 4.648, the depressing score was 5.611, the boring score was 6.149 and the beautiful score was 4.088. The high value of the negative urban perception score (depressing and boring score) and the low value of the positive urban perception score (wealthy, safe, lively and beautiful score) indicated that street level urban perception in Haidian District, Beijing was of a relatively low quality.

3.2. Multilevel model results

Models 1–4 in Table 2 were the main models, showing the relationship between street view urban perception and respondents' health outcomes. Model 1 shows the relationship between street view urban perception and respondents' GDS scores. GDS scores decreased with respondents' perception of safe scores [Coeff. = −0.187, SE = 0.085] and beautiful scores [Coeff. = −0.146, SE = 0.070] but increased with the perception of depressing scores [Coeff. = 0.199, SE = 0.087]. For other covariates, GDS scores decreased with

Table 2
Results from multilevel regression models for the relationship between health outcomes and neighborhood street urban perception among older adults.

	Model 1 (DV: GDS score)	Model 2 (DV: GAI score)	Model 3 (DV: SRH)	Model 4 (DV: Chronic diseases)
	Coef. (SE)	Coef. (SE)	OR. (95% CI)	IRR. (95% CI)
Fixed part				
Perceptual indicators				
Wealthy	−0.265 (0.248)	−0.016 (0.017)	0.987** (0.722–0.989)	0.871** (0.553–0.914)
Safe	−0.187** (0.085)	−0.021** (0.008)	0.862** (0.692–0.957)	0.711** (0.705–0.880)
Lively	−0.124 (0.212)	−0.020 (0.019)	0.927** (0.818–0.983)	0.859 (0.711–1.901)
Depressing	0.199** (0.087)	0.017** (0.008)	1.237 (0.918–1.454)	1.208 (0.693–1.954)
Boring	0.156 (0.126)	0.058 (0.079)	1.155** (1.006–1.261)	1.191** (1.022–1.244)
Beautiful	−0.146** (0.070)	−0.024*** (0.007)	0.874 (0.735–1.053)	0.869 (0.727–1.912)
Controlled variables				
Gender (ref: female)	0.040 (0.164)	−0.598** (0.269)	0.639 (0.414–1.088)	0.946 (0.847–1.056)
Age	−0.042*** (0.013)	−0.079*** (0.021)	1.011 (0.979–1.042)	0.997 (0.988–1.005)
Education (ref: primary school)				
High school	0.128 (0.196)	0.053 (0.320)	0.907 (0.618–1.641)	1.097 (0.959–1.255)
College and above	−0.017 (0.236)	−0.240 (0.377)	1.194 (0.684–2.085)	1.240*** (1.059–1.451)
Minority (ref: Han Chinese)	0.070 (0.392)	0.850 (0.636)	0.902 (0.304–2.674)	0.772* (0.581–1.027)
Marital status (ref: single)				
Married living with spouse	−0.332 (0.196)	−0.331 (0.321)	1.094 (0.686–1.744)	0.887* (0.776–1.013)
Married not living with spouse	0.403 (0.759)	0.153 (1.241)	0.860 (0.099–7.441)	0.839 (0.492–1.430)
Local hukou (ref: non)	0.420 (0.314)	0.534 (0.503)	1.104 (0.476–2.563)	1.230* (0.981–1.541)
Functional ability (ref: not restricted)	0.922*** (0.162)	1.155*** (0.263)	1.174*** (1.108–1.282)	1.007 (0.902–1.125)
Population density	0.001 (0.008)	0.002 (0.010)	1.131 (0.885–2.668)	1.042 (0.899–1.098)
Land use mix	−0.081 (0.435)	−0.552 (0.542)	0.937 (0.758–1.280)	0.931 (0.701–1.237)
Intersection density	−0.003 (0.006)	−0.004 (0.007)	0.902 (0.735–1.014)	0.996* (0.992–1.002)
Constant	7.542*** (1.143)	9.591*** (1.714)	2.957 (0.145–121.573)	3.158*** (1.514–6.584)
Random part				
Variance (neighborhood-level constant)	0.807**	0.192**	0.033**	0.029**
Variance (residuals)	6.232**	16.941**		
Number of respondents	1231	1231	1231	1231
Number of neighborhoods	48	48	48	48
AIC	5816.423	7020.051	5011.510	4835.343

* $p < .10$.
** $p < .05$.
*** $p < .01$.

respondents' age. Respondents who were functionally restricted also had higher GDS scores. Model 2 shows the relationship between street view urban perception and respondents' GAI scores. GAI scores decreased with respondents' perceptions of safe scores [Coeff. = −0.021, SE = 0.008] and beautiful scores [Coeff. = −0.024, SE = 0.007] but increased with perceptions of depressing scores [Coeff. = 0.017, SE = 0.008]. For other covariates, compared with females, male had lower GAI scores. GAI scores decreased with respondents' age. Respondents who were functionally restricted also had higher GAI scores. Model 3 shows the relationship between street view urban perception and respondents' SRH. Respondents' odds of reporting poor or very poor self-rated physical health decreased with respondents' perception of wealthy scores [OR. = 0.987, 95% CI = 0.772–0.989], safe scores [OR. = 0.862, 95% CI = 0.692–0.957] and lively scores [OR. = 0.927, 95% CI = 0.818–0.983] but increased with the perception of boring scores [OR. = 1.155, 95% CI = 1.006–1.261]. For other covariates, respondents who were functionally restricted had higher odds of reporting poor or very poor self-rated physical health. Model 4 shows the relationship between street view urban perception and respondents' incidence rate ratios of having chronic diseases. Respondents' incidence rate radios of having chronic diseases decreased with respondents' perception of wealthy scores [IRR. = 0.871, 95% CI = 0.553–0.914] and safe scores [IRR. = 0.711, 95% CI = 0.705–0.880] but increased with perception of boring scores [IRR. = 1.191, 95% CI = 1.022–1.244]. For other covariates, compared with respondents with a primary school and lower educational attainment, respondents with college and higher levels of educational attainment had higher incidence rate ratios of having chronic diseases.

Models 5–7 in Table 3 were used to test whether the results in Models 1–4 were robust. In Model 5a–5d, we set the radius of the buffer as 2000 m. In Model 7a–7d, we excluded respondents aged 85 years and above because these respondents with an extremely old age might have a biased perception of the street view (Gascon et al., 2018). In Model 6a–6d, we excluded respondents who had problems with traversing 3–4 miles on foot or going up and down stairs unaided because these respondents were less likely to walk around their neighborhood and were less influenced by street view urban perceptions. For all these robustness tests models, the relationship between neighborhood street view perception and respondents' outcomes was significant and compared with residents living in neighborhoods in the first quartile of street view greenness. Additionally, GDS as well as GAI scores decreased with respondents' perceptions of safe scores and beautiful scores but increased with perceptions of depressing scores. Respondents' incidence rate radios of having chronic diseases decreased with respondents' perceptions of wealthy scores and safe scores but increased with perceptions of boring scores. Additionally, respondents' odds of reporting poor or very poor self-rated physical health decreased with their perception of wealthy scores, safe scores and lively scores but increased with perceptions of boring scores.

4. Discussion

This is the first study to associate perceptions of a large-scale urban area from street view images in conjunction with a deep learning technique with various health outcomes for older adults. The results show a potential positive effect of positive urban perception (e.g., safe) on health outcomes for older adults, as well as a potential negative effect of negative urban perception (e.g., depressing). The results were validated, as shown in several robust tests.

Compared with previous studies (Dubey et al., 2016; Naik et al.,

Table 3
Robustness of the tests results from multilevel regression models for the relationship between health outcomes and neighborhood street urban perception among older adults.

	DV: GDS score	DV: GAI score	DV: SRH	DV: Chronic diseases
	Coef. (SE)	Coef. (SE)	OR. (95% CI)	IRR. (95% CI)
	Model 5a	Model 5b	Model 5c	Model 5d
Perceptual indicators				
Wealthy	−0.142 (0.211)	−0.018 (0.030)	0.918** (0.859–0.975)	0.981** (0.165–0.991)
Safe	−0.125** (0.057)	−0.015** (0.007)	0.937** (0.824–0.991)	0.990** (0.852–0.997)
Lively	−0.117 (0.215)	−0.015 (0.023)	0.922** (0.831–0.966)	0.976 (0.913–1.059)
Depressing	0.099** (0.042)	0.027** (0.012)	1.009 (0.899–1.062)	1.047 (0.937–1.110)
Boring	0.102 (0.084)	0.054 (0.063)	1.119** (1.005–1.252)	1.034** (1.009–1.126)
Beautiful	−0.156** (0.075)	−0.024** (0.011)	0.989 (0.885–1.115)	0.973 (0.834–1.133)
	Model 6a	Model 6b	Model 6c	Model 6d
Perceptual indicators				
Wealthy	−0.125 (0.237)	−0.025 (0.021)	0.943** (0.919–0.993)	0.916** (0.843–0.933)
Safe	−0.112** (0.053)	−0.018** (0.007)	0.965** (0.878–0.988)	0.923** (0.880–0.973)
Lively	−0.133 (0.215)	−0.022 (0.029)	0.899** (0.842–0.975)	0.916 (0.834–1.047)
Depressing	0.079** (0.035)	0.018** (0.008)	1.009 (0.862–1.083)	1.046 (0.833–1.113)
Boring	0.142 (0.091)	0.031 (0.090)	1.127** (1.085–1.315)	1.044** (1.009–1.098)
Beautiful	−0.141** (0.066)	−0.048** (0.022)	0.954 (0.825–1.111)	0.990 (0.865–1.089)
	Model 7a	Model 7b	Model 7c	Model 7d
Perceptual indicators				
Wealthy	−0.149 (0.213)	−0.017 (0.019)	0.945** (0.922–0.981)	0.945** (0.832–0.985)
Safe	−0.125** (0.061)	−0.018** (0.008)	0.943** (0.914–0.952)	0.965** (0.871–0.974)
Lively	−0.142 (0.226)	−0.023 (0.030)	0.944** (0.915–0.982)	0.955 (0.885–1.042)
Depressing	0.093** (0.042)	0.017** (0.007)	1.033 (0.899–1.032)	1.008 (0.891–1.071)
Boring	0.116 (0.076)	0.020 (0.071)	1.105** (1.003–1.231)	1.065** (1.002–1.096)
Beautiful	−0.132** (0.065)	−0.055** (0.026)	0.978 (0.901–1.057)	0.912 (0.801–1.056)

Models adjusted for individual-level and neighborhood-level covariates.
** $p < .05$.

2014; Salesses et al., 2013), our human-machine adversarial scoring achieved a high accuracy and the reasons may be as follows: First, previous studies mainly based on Place Pulse 1.0 dataset which contains street view images all over the world but their study area was within a single country, so the training dataset may mismatch with testing dataset. However, our training and testing dataset were both collected in mainland China, so it ensured the consistency between training and testing dataset. Second, we used a human-machine adversarial scoring approach which can be regarded as a calibration method, so it further ensure the performance of our model. Third, RF adopts a large number of weak decision trees to vote, and makes decisions according to the voting structure which can help it resist the high-dimensional nonlinear fitting/classification problem (Fernández-Delgado, Cernadas, Barro, & Amorim, 2014; Liaw & Wiener, 2002). Therefore, the correlation between variables will not affect the results, and RF will not produce overfitting (Fernández-Delgado et al., 2014; Liaw & Wiener, 2002). Hence, RF is widely used in the field of geoscience, and the combined effect with CNN has achieved high accuracy (Yao, Zhang, Hong, Liang, & He, 2018).

Among all urban perceptual indicators, safety is significantly associated with all health outcomes, and this can be explained by both SRT and ART. First, SRT indicates that the sense of safety may awaken “evolutionary adaptation” and “biologically adaptation”, which are important people to survive (Ulrich et al., 1991). “Evolutionary adaptation” indicates that perceived safety prevents people from a fear of being hurt in certain environments, while “biological adaptation” suggests that the perceived safety makes people believe they can get help when they are in need in a certain environment (Ulrich et al., 1991). Second, ART indicates that when a certain environment provides people with a sense of security, it may help them recover from daily stressful events, so the perception of safety may be a buffer between daily stressors and people's well-being by reducing stress (Kaplan, 1995).

The perception of depression and beauty were significant related to mental health for older adults. The perception of depression is directly related to residents' mental state because a depressing environment may increase residents' psychological pressure during exposure to such an environment for a long time. The prolonged psychological pressure can accumulate and lead to depression and anxiety (Mahmoud, Staten, Hall, & Lennie, 2012; Shamsuddin et al., 2013). Additionally, ART and SRT indicate that a beautiful environment can be regarded as a recovery setting that reduces stress and restores attention, so during exposure to such an environment, people may recover from stress and show improvements in positive moods. Previous studies have demonstrated that residents living in more beautiful and greener neighborhoods tend to participate in more outdoor physical activities (Lu, 2018; Lu, Sarkar, & Xiao, 2018) and stronger social cohesion (De Vries, van Dillen, Groenewegen, & Spreeuwenberg, 2013). In addition, people with low socioeconomic status tend to rely heavily on public green spaces in neighborhoods, while people with high socioeconomic status often purchase green space services privately in China (Xiao, Lu, Guo, & Yuan, 2017). Therefore, the perception of beauty may have a strong effect on the mental health of older adults, typically with low socioeconomic status.

Furthermore, perceptions of wealth, bore and liveliness were significantly related to physical health in older adults. People's perceptions of wealth may reflect the socioeconomic status of a neighborhood, so older adults living in neighborhoods with higher level of perceived wealth are more likely to enjoy better public facilities and well-maintained environments. In addition, perceptions of bore and liveliness indicate the vitality of a neighborhood, so during exposure to a neighborhood with higher levels of perceived bore and lower levels of liveliness, older adults may be less stimulated to go outdoors (Björk et al., 2008; Marquet & Miralles-Guasch, 2015). Moreover, living in such neighborhoods, they may reduce their social interactions by adopting a more sedentary lifestyle because they may acquire less health-related information from others (Kawachi et al., 1999).

In summary, the results revealed some positive perceptions, including wealthy, safe, lively and beautiful, are beneficial for health outcomes for older adults, while some negative urban perceptions, including boring and depressing, may have an adverse effect on health outcomes. Two possible potential mechanisms should be proposed. First, positive urban perceptions of the built environment may decrease mental stress, while negative urban perceptions may increase mental stress, which may become a long-term stressor and cause endocrine disorders and long-term health problems (Pearlin, Schieman, Fazio, & Meersman, 2005; Slaski & Cartwright, 2003). Second, perceptions of the built environment may also have influence older resident's health-related behaviors, including physical activities and social interactions. This phenomenon can be explained by the Mehrabian-Russell Model theory, which suggests that human perceptions of the urban environment may influence our emotions and feelings, and emotions and feelings may subsequently affect our behavioral choices (Mehrabian & Russell, 1974). Positive urban perceptions may encourage residents to participate in more health-related behaviors and promote their health, while negative urban perceptions may decrease residents' health-related behaviors and have a negative influence on their health (Parsons, 1991). Since our human-machine confrontation scoring system was trained by feeding the proportion of 151 elements in the image segmentations, consistent with previous studies (Zhang et al., 2019), we further found that specific elements including building, car, tree, grass and sky account for the largest weight which indicates that these elements have significant influence on people's perception. Buildings and sky have influence on visual enclosure (Wang, Lu, et al., 2019), greenspace can reduced stressful feelings (Kaplan, 1995; Ulrich et al., 1991), and cars are related to noise and crowd (Zhang et al., 2019), so they all can affect people's mental state. In essence, urban perception reflects people's feelings towards ground objects, so policy makers should pay attention to the visual proportion of different ground objects.

This study focused on older adults because Beijing and many cities in China are facing the challenges of an aging population. The results of this study show more significant and robust urban perception–health associations for older adults compared with young adults in previous studies (Parsons, 1991; Rollero & De Piccoli, 2010), which may be explained by different environmental exposures and a sense of attachment to a place for older and young adults. First, older adults may have limited mobility and spend most of their time around their homes. In contrast, young adults' daily environmental exposure includes their neighborhood, working place and places for leisure purposes (Helbich, 2018; Pearce et al., 2016; Schönfelder & Axhausen, 2003). Hence, older adults are more susceptible to the neighborhood environment compared with young people. Second, older adults have a stronger sense of place attachment to the neighborhood than young people because it is their most important social space (Wiles et al., 2009; Wiles et al., 2012). Therefore, perceptions of the neighborhood environment may have a stronger effect on older than on young adults.

The current study further contributes to the methodological development of health studies. Perceptions of the built environment are often collected using questionnaires in empirical studies, which are expensive, time-consuming and limited to a small sample size. With the free street view images and machine-learning method, we can effectively obtain the perceptions of a large-scale study region, such as a whole city. This is one of the first studies to use the Tencent Street View to investigate the associations of perceptions of street view images and various health outcomes for a relatively large sample size for older adults in China. The large sample of training data and advanced machine learning methods guaranteed the accuracy of the perception data.

However, some limitations should be noted. First, we used the semantic objects to feed the classifier and this may reduce the performance of it since substantial and detailed information will get lost in segmentations process. Further research may consider other process which may contain more detailed information for original images. Second, the cross-sectional study design precludes inferences of a causal relationship between perceptions of the built environment and older adults' health. Further studies may consider the natural experimental research design to produce high-quality evidence to inform policy decisions. Third, the study sample is not sufficiently representative because Beijing is one of the most developed cities in China, and thus the relationship to older adults in rural areas or underdeveloped areas in China is still unclear. Hence, although previous studies indicated that age and location difference of the training participants may not cause bias, the age and location mismatch in our research may still cause some errors. Fourth, we have not explored the underlying mechanisms between perceptions of the built environment and health outcomes. Fifth, this study is also limited due to the Modifiable Area Unit Problem (MAUP) because independent variables were collected using one buffer size of 1 km. Although in robustness tests we used a different buffer size of 2 km, this was still not sufficient to avoid the effect of MAUP. Sixth, we only focused on six urban perceptual indicators because the accuracy of these indicators from street view images has been validated in previous studies and they cover most aspects of perceptions of the built environment. However, some aspects of perceptions of the built environment are missing in the current studies, such as loneliness.Still, identifying additional indicators on people's concepts related to urban features would provide valuable information for enhanced spatial and urban planning and is scheduled for future research. Seventh, in this approach we do not take into account spatial dependence. A way to do so is by applying spatial econometric models. These models provide evidence of whether space has an effect on the dependent or the independent variables. Testing various spatial econometric models such as Spatial Autoregressive Models, or Spatial Error Models is necessary and is planned for future research. Still, in these models the spatial component may reside in either the dependent side or the independent side of the equation which makes models' interpretation more complex. As in the current research we are primarily interested in identifying if and how the various built environment perceptions have an effect on health, we prefer applying multilevel regression where results' interpretation and variables linkages are more straightforward. Eighth, to avoid any potential alternation in people's perceptions regarding the various neighborhood indicators due to rapid urbanization trough time, images should refer, ideally, to the same time with the time that the health survey was conducted. In this study, images refer to one year later (2012) than the year of the health survey (2011). Although this is a limitation, we expect that the bias inferred by urbanization in neighborhood perceptions indicators would be minimum, and would not significantly affect the validity of our approach. Also, we assumed that volunteers' perception of neighborhood is similar to respondents. However, the period volunteers scored images is also mismatch with survey data and people's perception of neighborhood may also vary in different period. Last, we did not fully use geospatial information of street view data such as the agglomeration of the same kind of perception.

5. Conclusion

The present study demonstrated a significant relationship between respondents' perceptions of the built environment and their health outcomes for older residents in Beijing, China. The results also confirm that the perception of safety was significantly associated with all health outcomes. Additionally, the perceptions of depression and beauty were significantly related to older adults's mental health, while perceptions of wealth, bore and liveliness were significantly related to their physical health. The findings were supported in several robustness tests. Further studies are required to address some of the remaining limitations of this research, including the use of a natural experimental design and elucidation of potential mediating mechanisms.

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Declaration of Competing Interest

None.

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