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Using street view data and machine learning to assess how perception of neighborhood safety influences urban residents' mental health

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ABSTRACT

Previous studies have shown that perceptions of neighborhood safety are associated with various mental health outcomes. However, scant attention has been paid to the mediating pathways by which perception of neighborhood safety affects mental health. In addition, most previous studies have evaluated perception of neighborhood safety with questionnaires or field audits, both of which are labor-intensive and time-consuming. This study is the first attempt to measure perception of neighborhood safety using street view data and a machine learning approach. Four potential mediating pathways linking perception of neighborhood safety to mental health were explored for 1029 participants from 35 neighborhoods of Guangzhou, China. The results of multilevel regression models confirm that perception of neighborhood safety is positively associated with mental health. More importantly, physical activity, social cohesion, stress and life satisfaction mediate this relationship. The results of a moderation analysis suggest that the beneficial effects of physical activity and social cohesion on mental health are strengthened by a perception of neighborhood safety. Our findings suggest the need to increase residents' perception of neighborhood safety to maintain mental health in urban areas of China.

1. Introduction

Globally, many countries have undergone or are undergoing urbanization, which is having a great impact on the mental health of urban residents. The proportion of China's population that is urban, grew from 17.9% in 1978 to 58.5% in 2017 (NBSC, 2018). Associated with this rapid urbanization, the annual burden of mental disorders in urban China will increase by 10% (3.6 million disability-adjusted life-year) from 2013 to 2025 (Charlson et al., 2016). Compared with rural residents, urban residents are more likely to suffer from mental illness because of their limited exposure to a natural environment, the stressful nature of the built environment, weaker social ties and lower perceived safety (Chen and Chen, 2015; Hancock, 2001). Neighborhood safety has been recognized as a key factor influencing various health-related behaviors and health outcomes (Loukaitou-Sideris and Eck, 2007). Thus, a perceived lack of safety in a neighborhood environment may have negative effects on urban residents' mental well-being.

1.1. Effects of perception of neighborhood safety on mental health

Previous meta-reviews have identified four potential pathways through which perception of neighborhood safety can affect mental health: promoting physical activity, strengthening social cohesion, reducing psychological stress and improving life satisfaction (Won et al., 2016). First, a lack of perceived neighborhood safety discourages residents from engaging in outdoor physical activity because they may feel unsafe or uncomfortable outdoors (McGinn et al., 2008; Ruijsbroek et al., 2015; Li et al., 2005; Olvera et al., 2012; Ruijsbroek et al., 2015, 2015; Wilcox et al., 2003). Evidence also shows that a perception of safety is a prerequisite for residents to make use of natural environments such as the parks and public greenspaces in which most people routinely engage in physical activity (Weimann et al., 2017).

Second, residents who perceive their neighborhood as safe believe that they have a safe place to meet and socialize with their neighbors (De Jesus et al., 2010; Ruijsbroek et al., 2015; Won et al., 2016). With

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higher levels of perceived safety, residents are more likely to trust their neighbors and have frequent social interactions with them (De Jesus et al., 2010). Frequent social contact among neighbors can increase neighborhood social cohesion (Forrest and Kearns, 2001). Previous studies have found that neighborhood social cohesion benefits residents' mental health because people living in a cohesive neighborhood can acquire health-related information and support from their neighbors (Ziersch et al., 2005).

Third, a lack of perceived safety, as a source of fear, may increase feelings of vulnerability and psychological stress (De Donder et al., 2013). Daily exposure to an unsafe neighborhood environment may even undermine a person's immune system and increase susceptibility to disease (Glaser et al., 1999). Perceived neighborhood safety can help reduce stress and thus be a restorative factor (Hill et al., 2005).

Fourth, life satisfaction plays an important mediating role between perception of neighborhood safety and mental health (Leslie and Cerin, 2008; Ziersch et al., 2005). Residents' perception of neighborhood safety significantly affects their life satisfaction because they spend a large proportion of their time in their neighborhood (Feng et al., 2018; Ma et al., 2018). Previous studies suggest that life satisfaction is positively associated with mental health; it not only reflects the level of health-related quality of life but also affects residents' subjective evaluation of their quality of life (Grant et al., 2009; Strine et al., 2008).

1.2. Traditional methods of evaluating perceptions of neighborhood safety

Previous epidemiological studies mainly assessed the perceptions of neighborhood safety using questionnaires (Baum et al., 2009; Hong et al., 2018; Leslie and Cerin, 2008; Wilson-Genderson and Pruchno, 2013) or systematic social observations (SSO) (Jones-Rounds et al., 2014; Odgers et al., 2012; Schaefer-McDaniel et al., 2010a, 2010b; van Lenthe et al., 2005).

Using questionnaires is arguably the most common method to assess different dimensions of perceived neighborhood safety: including overall/general neighborhood safety, traffic-related safety, crime-related safety and proxies for safety (Won et al., 2016). With this method, investigators may ask respondents to score different aspects of neighborhood safety based on Likert scale (Baum et al., 2009; De Jesus et al., 2010; Hong et al., 2018; More et al., 2019; Özgüner et al., 2012; Ruijsbroek et al., 2015; Tamayo et al., 2016; Weimann et al., 2017; Wilson-Genderson and Pruchno, 2013). For example, De Jesus et al. (2010) used the question "how safe do you feel walking alone in your neighborhood?" in their study. Weimann et al. (2017) used "How safe and secure do you feel when you are walking alone in your neighbourhood after dark?". Wilson-Genderson and Pruchno (2013) used similar question "I feel safe being out alone in my neighborhood during the daytime and at night". The advantage of using questionnaire is that it can reflect respondents' perceived safety which may be more relevant to health outcomes than objectively measured safety, such as crime rate or number of traffic incidents (Won et al., 2016). However, this method becomes increasingly costly, labor-intensive and time-consuming for studies with larger sample size and study area because more trained investigators are needed. Also, it is usually difficult to interpret results related to perceived safety, for instance, which built environment characteristics may affect perceived safety.

Another method to assess perceptions of neighborhood safety is SSO, requiring researchers to walk or drive around a neighborhood and audit neighborhood safety with pre-defined survey forms (Schaefer-McDaniel et al., 2010a, 2010b). For example, Jones-Rounds et al. (2014) measured perceptions of neighborhood safety by trained raters and found neighborhood safety was positively related to psychological well-being. Mayne et al. (2017) also measured perceptions of neighborhood safety with SSO and found neighborhood safety was associated with lower smoking rate, but not with social cohesion. The main contribution of SSO is that the perceived safety among different neighbourhood is comparable because it is assessed by the same group of raters. Also, when rating neighbourhoods, trained raters may also take photos or videos, so the neighbourhood characteristics affecting perceived safety can be further identified. However, the main methodological drawback of SSO is labor-intensive and time-consuming because a team of trained raters need to traverse through all study areas. Thus, it is not suitable for large-scale studies.

1.3. Research gaps and our novel approach

Most research evidence of the beneficial effect of a perception of neighborhood safety on mental health comes from studies conducted in developed countries, such as the United States and Australia. Scarce evidence is available from developing countries, such as China, although the mental health burden is heavy in many Chinese cities. A few studies have found a positive association between perception of neighborhood safety and mental health in some Chinese cities (Chen and Chen, 2015; Chen et al., 2013; Wen et al., 2010). However, these studies failed to systematically examine the pathways through which perception of neighborhood safety influences mental health. Moreover, these previous studies measured perception of neighborhood safety using either questionnaires or traditional SSO.

To overcome the limitations of questionnaire and SSO methods, some researchers begun to use street view data to measure perceived safety (Dubey et al., 2016; Salesses et al., 2013; Yao et al., 2019; Zhang et al., 2018). Some researchers advocate conducting virtual SSO via street view images, such as Google Street View, to save time and cost (Boulos et al., 2019; Odgers et al., 2012; Rzotkiewicz et al., 2018). With the help of street view images, researchers can conduct SSO remotely and do not need to physically visit the study areas (Odgers et al., 2012; Rzotkiewicz et al., 2018). Although assessing perception of neighborhood safety based on SSO and street view images can improve efficiency, it has some drawbacks. First, this method needs researchers to score each image, which limits the total number of assessed images. Second, the number of images used to evaluate a study area is limited, so the selected images may not represent the whole neighborhood.

Some researchers propose to automatically assess neighborhood safety by combining street view data with machine learning techniques. For example, Zhang et al. (2018) combined street view data with Support Vector Machine and mapped residents' perception of safety in Beijing, China. The advantage of using street view data to assess perceived safety is that street view data are freely and readily available for many global cities. Therefore, this novel method to assess perceived safety is more time- and cost-effective, compared with the method of questionnaire and traditional SSO. However, no studies have used this innovative method in epidemiologic study, so feasibility of this method in empirical studies is still unknown.

In this study, we used street view images in conjunction with deep learning to assess perceived safety, and explored four potential pathways linking perception of neighborhood safety with mental health among residents of 35 neighborhoods of Guangzhou, China. This innovative method can accurately and automatically rate overall safety for a large number of images based on a subset of training images assessed by human raters (Naik et al., 2014; Salesses et al., 2013; Wang et al., 2019b; Zhang et al., 2018; Wang et al., 2019c). Furthermore, with the detailed ground object information in street view data, we can potentically identify which neighbourhood characteristics may affect people's perceived safety. We believe this study can further advance methodological development in epidemiologic studies by overcoming some limitations of traditional methods of questionnaires and SSO.

2. Data and methods

2.1. Data

The survey data used in this study were collected in Guangzhou between June and August 2016. Thirty-five residential neighborhoods (average area = 1.91 km^2, average population = 4155 persons) were randomly chosen from six urban districts of Guangzhou (Yuexiu, Haizhu, Panyu, Baiyun, Tianhe and Liwan) based on a multi-stage stratified sampling technique. In the second stage, 30 households from each sampled neighborhood were randomly selected. In the final stage, we selected one household member from each household. This method yielded a total of 1029 valid participants.

2.2. Variables

2.2.1. Outcomes

We used the World Health Organization Well-Being Index (WHO-5) to measure respondents' mental health (Topp et al., 2015). The WHO-5 includes five items to assess respondents' mental health-related feelings over the previous two weeks. Each item is scored on a six-point Likert scale, ranging from "at no time" to "all of the time." The total WHO-5 index score ranges from 0 to 25. The WHO-5 has been proven to have good validity and reliability in different countries, with a Cronbach's alpha of 0.82 (Krieger et al., 2014).

2.2.2. Perception of neighborhood safety

The neighborhood area was defined as 1 km circular buffer around a resident's home. The street view images used for this study were collected from Tencent Map, one of the largest online map services in China. We followed the method of Long and Liu (2017) to retrieve Tencent street view images. We then constructed sampling points for the images at 100-m spacing along the road network, based on OpenStreetMap (Haklay and Weber, 2008). For each sampling point, we retrieved four street view images (with directions of 0, 90, 180 and 270 degrees, respectively), to collect panoramic streetscape views. On average, we obtained 526.5 sampling points and 2105.9 images (SD = 768.0) per neighborhood.

We then applied a fully convolutional neural network (FCN-8s) to segment the street view images into common types of object (e.g., trees, buildings and people), so that we could identify objects from the images (le Cun et al., 2015; Long et al., 2015). To train the convolutional neural network, we used a collection of annotated images from the ADE20K database (Zhou et al., 2017, 2019a,b). This method has been proven to be efficient in identifying objects in epidemiological studies (Helbich et al., 2019; Lu et al., 2018; Wang et al., 2019a, 2019b, 2019c). After the image segmentation, 30 volunteers (mean age = 35.68 years) who were either university students or employees were asked to score the images (3000 street view images in total) on general perception of safety (from 0–10 points). Before using the scoring system, all volunteers were given an operation manual and received adequate training on using the scoring system. Next, we used a random forest model (Breiman, 2001) for automatic rating; the model was trained by fitting the safety scores of the 3000 images based on the proportion of different types of objects in images. For example, a lower proportion of pedestrians may lead to a lower safety score, because the presence of pedestrians could deter criminal and anti-social behaviors (Naik et al., 2014; Weidemann et al., 1982). The trained random forest model was then used to predict safety scores of other images.

To improve the accuracy of our identifying model, we used a human–machine adversarial scoring approach for some additional images. First, the results of image segmentation were provided to the volunteers,. Second, the above trained random forest model was used to automatically calculate the safety scores of images based on the proportion of different types of objects in images. Third, volunteers were asked to correct the recommended scores of these images to further calibrate the trained model. The calibrating process stopped when the recommended scores given by the model and those of the volunteers reached a high level of agreement (a root mean square error of < 5 for the previous 100 images). Thus, after the above process, we acquired a more accurate automatic scoring model. Fig. 1 summarizes the workflow.

Finally, we validated the accuracy and reliability of the calibrated model. One hundred street view images were randomly selected, and perceptions of safety were assessed by both our model and five human volunteers. The safety scores given by the model were highly correlated with those of the volunteers ($r = 0.98$, $p < 0.05$).

Perceptions of safety for all street view images in Guangzhou could thus be automatically assessed using this scoring model based on machine learning. Safety scores per sampling point were calculated from the average of safety scores for four images in different cardinal directions (0, 90, 180 and 270 degrees). For each neighborhood, we calculated the mean safety scores per sampling point within a 1 km buffer.

2.2.3. Mediators

Four potential pathways were assessed: promoting physical activity, strengthening social cohesion, reducing psychological stress and improving life satisfaction. All mediators were adopted from the survey questionnaire. The first mediator was the amount of time per week spent on physical activity. The second was neighborhood social cohesion. Following previous studies (de Vries et al., 2013; Ruijsbroek et al., 2015), we used six statements concerning respondents' perceptions of social cohesion to measure neighborhood social cohesion: "people in this neighborhood are willing to help each other", "people in this neighborhood often visit each other's house", "people in this neighborhood are trustworthy", "people in this neighborhood greet each other", "people can deal with problems in the neighborhood together" and "people in this neighborhood often exchange health information with each other" (Cronbach's alpha = 0.82). Answers ranged from "strongly disagree" to "strongly agree" on a five-point Likert scale. Individuals' mean scores on these items were used as a social cohesion score.

The third mediator was stress, which we measured with the following question: "How often did emotional stress affect your work and daily activities in the past month?" (never = 1; seldom = 2; sometimes = 3; often = 4; always = 5). The final mediator was life satisfaction, which was measured with the following question: "How satisfied are you with your quality of life in this neighborhood?" (very unsatisfied = 1; unsatisfied = 2; neutral = 3; satisfied = 4; very satisfied = 5).

2.2.4. Covariates

We adjusted for a series of covariates including gender, age, marital status, *hukou* status, education attainment, household wealth, household size, physical functional status, length of residence in the neighborhood, medical insurance participation, current smoking status and current drinking status. The summary statistics for all variables are shown in Table 1.

2.3. Data analysis

To assess the linkage between perception of neighborhood safety and mental well-being, we fitted multilevel linear regression models (Raudenbush and Bryk, 2002). Multilevel models were preferred over single-level models due to the hierarchical structure of our data (i.e. residents were nested in neighborhoods). Variance inflation factors < 3 suggested a lack of severe multicollinearity among predictors. The intra-class correlation coefficient for the null model (0.33) confirmed the need for a multilevel model, suggesting that living within the same neighborhood accounted for 33 percent of the total variance in respondents' WHO-5 index.

We tested the existence of four pathways using Baron and Kenny (1986)'s mediation analysis. First, we regressed WHO-5 index on perception of neighborhood safety and covariates (Model 1). Second, we regressed each of the four mediators on perception of neighborhood safety and covariates (Models 2a-d). Third, we regressed WHO-5 index on perception of neighborhood safety, covariates and mediators that

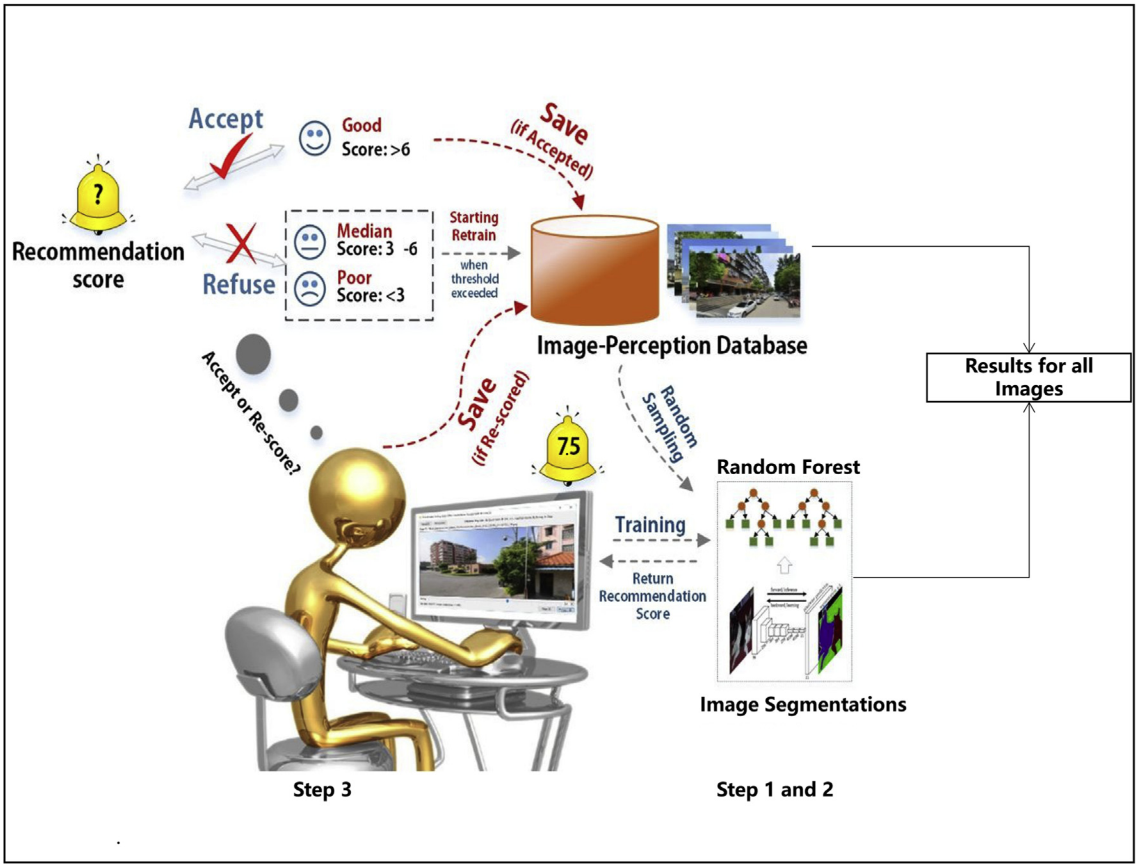

Fig. 1. Workflow for assessing the perception of safety in street view images.

were significantly associated with perception of neighborhood safety (Models 3–7). Fourth, we tested whether mediation effects were statistically significant using tests proposed by Sobel (1982) and Preacher and Hayes (2008). In addition, cross-level interaction terms between perception of neighborhood safety and significant mediators were added to Model 7 to examine whether perception of neighborhood safety moderates the relationship between mediators and mental well-being (Model 8).

3. Results

3.1. Relationship between perception of neighborhood safety and mental well-being

Table 2 presents the results of Model 1. The respondents' mental well-being was positively associated with perception of neighborhood safety (Coef. = 0.278, SE = 0.106). Men had higher WHO-5 scores than women (Coef. = 0.785, SE = 0.294). Respondents who were married reported lower WHO-5 scores (Coef. = −0.600, SE = 0.277). Those who suffered from functional limitations and those who were current drinkers had lower WHO-5 scores (Coef. = −1.561, SE = 0.499; Coef. = −0.710, SE = 0.310).

3.2. Relationships between perception of neighborhood safety and potential mediators

Table 3 illustrates the extent to which perception of neighborhood safety is associated with each of the four potential mediators. Models 2a, 2c and 2d showed that the amount of time spent on physical activity, neighborhood social cohesion and life satisfaction were positively related to perception of neighborhood safety (Coef. = 0.029, SE = 0.014; Coef. = 0.036, SE = 0.013; Coef. = 0.021, SE = 0.002). Model 2b showed that stress was negatively related to perception of neighborhood safety (Coef. = −0.059, SE = 0.022).

3.3. Mediating effect of physical activity, social cohesion, stress and life satisfaction

Given that all four mediators were found to be significantly linked to perception of neighborhood safety, we examined the extent to which the relationship between neighborhood safety and mental well-being was mediated by physical activity, social cohesion, stress and life satisfaction (See Table 4). When any or all of the four mediators were added to Model 1 (Models 3–7), the association between perception of neighborhood safety and mental well-being became substantially weaker. The results of Sobel's test confirmed that physical activity, social cohesion, stress and life satisfaction played a mediating role in the neighborhood safety–mental well-being relationship (physical activity: Z score = 1.979, p-value = 0.048; social cohesion: Z score = 2.705, p-value = 0.007, stress: Z score = 2.421, p-value = 0.015, life satisfaction: Z score = 2.108, p-value = 0.035). The results of the test proposed by Preacher and Hayes (2008) for multiple mediation analysis confirmed that both physical activity and social cohesion had a partial mediation effect on the neighborhood safety–mental well-being relationship (Z score = 1.986, p = 0.047).

We then added interaction terms to Model 7 to examine the extent to which perception of neighborhood safety moderates the relationship between any of the four mediators and mental well-being (Model 8). Perception of neighborhood safety moderated the relationships between physical activity, social cohesion and mental well-being, but no moderation effect was found for stress or life satisfaction. This suggests that a higher perception of neighborhood safety strengthens the beneficial effect of physical activity and neighborhood social cohesion only.

Table 1
Summary statistics for all variables.

Variables	Proportion/Mean (SD)
Dependent variable	
WHO Score (0–25)	12.081 (3.706)
Independent variable	
Neighborhood safety (0–10)	4.719 (0.448)
Mediators	
Physical activity (hours/week)	4.024 (4.182)
Social cohesion (0–5)	2.948 (0.582)
Life satisfaction (0–5)	3.764 (0.709)
Stress (0–5)	1.798 (0.808)
Controlled variables	
Gender (%)	
Male	50.146
Female	49.854
Age	41.185 (13.576)
Marital status (%)	
Single, divorced or widowed	21.672
Married	78.328
Hukou status (%)	
Local *hukou*	77.745
Non-local *hukou*	22.255
Educational attainment (%)	
Primary school or below	2.527
High school	50.048
College or above	47.425
Household wealth	
Group 1 (10,000 yuan or below)	7.192
Group 2 (10,000–20,000 yuan)	70.651
Group 3 (20,000–40,000 yuan)	15.258
Group 4 (40,000 yuan or above)	6.899
Household size (persons)	3.282 (0.852)
Length of residence in the neighborhood (years)	13.206 (11.022)
Functionally restricted (%)	
Yes	3.984
No	96.016
Medical insurance (%)	
Have medical insurance	97.085
No medical insurance	2.915
Smoking (%)	
Current smoker	26.433
Non-smoker	73.567
Drinking (%)	
Drinker	41.108
Non-drinker	58.892

Table 2
The association between perception of neighborhood safety and mental well-being.

	Model 1
	Coef. (SE)
Fixed part	
Neighborhood safety	0.278*** (0.105)
Male (ref: female)	0.785*** (0.294)
Age	−0.005 (0.010)
Married (ref. = single, divorced or widowed)	−0.600** (0.277)
Local *hukou* (ref: non-local *hukou*)	−0.254 (0.233)
Education (ref: primary school or below)	
High school	0.295 (0.632)
College and above	1.190* (0.675)
Household wealth (ref: Group 1)	
Group 2	−0.078 (0.387)
Group 3	0.110 (0.459)
Group 4	0.186 (0.513)
Household size	−0.228* (0.123)
Length of residence in the neighborhood	−0.001 (0.011)
Functionally restricted (ref: not restricted)	−1.561*** (0.499)
Medical insurance (ref: no medical insurance)	−0.093 (0.575)
Drinking (ref: do not drink)	−0.710** (0.310)
Smoking (ref: nonsmoker)	−0.350 (0.250)
Constant	−0.016 (5.271)
Random part	
Var (neighborhoods)	4.274***
Var (individuals)	7.775***
Number of individuals	1029
Number of neighborhoods	35
Log likelihood	−2519.054
AIC	5076.11

Note: Coef. = coefficient; SE = standard error; AIC = Akaike information criterion. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

4. Discussion

This study extends previous research on the association between perception of neighborhood safety and mental health in several respects. It is the first to systematically explore several potential mediating pathways linking perception of neighborhood safety and mental health. It also makes a methodological contribution to health studies by using street view data and a machine learning approach to measure perceived safety. This new approach is more time- and cost-effective than field audits or questionnaires.

The results confirm all four mediating pathways between perception of neighborhood safety and mental health: physical activity, neighborhood social cohesion, psychological stress and life satisfaction. First, several reviews have suggested physical activity as a potential pathway linking perception of neighborhood safety and health outcomes (Lorenc et al., 2012; Won et al., 2016). Much empirical evidence has demonstrated that a perception that their neighborhood environment is safe encourages residents to engage in physical activity (Ball et al., 2008; Cerin et al., 2013; de Farias Júnior et al., 2011; Wendel-Vos et al., 2007). However, scant evidence is available to support the mediating role of physical activity in the relationship between perceived safety and health outcomes. Our finding contradicts that of a study conducted in the Netherlands (Ruijsbroek et al., 2015), which did not find evidence that perceived safety was associated with health benefits achieved through an increase in physical activity. One possible reason for this difference is the different health outcomes assessed in these studies. Ruijsbroek et al. (2015) used self-rated general health as the health outcome, while this study focused on mental health. Perception of neighborhood safety may be more relevant to mental health than to general health because perceptions are directly associated with personal feelings and emotions (Won et al., 2016). Furthermore, Chinese urban residents usually take physical activity in their neighborhood (Ng et al., 2009), so they may have longer exposure to their neighborhood environment than their counterparts in the Netherlands.

Second, previous reviews have reported the mediating role of neighborhood social cohesion (Lorenc et al., 2012; Won et al., 2016), yet only a few examples of empirical evidence have been provided (De Jesus et al., 2010; Ruijsbroek et al., 2015). Consistent with previous studies (De Jesus et al., 2010; Ruijsbroek et al., 2015), we found that a perception of neighborhood safety benefits residents' mental health by improving social cohesion within the neighborhood. This finding confirms the assumption that a safe neighborhood offers residents a favorable place to interact with their neighbors and participate in neighborhood activities, both of which in turn benefit their mental health (Ziersch et al., 2005). In addition, studies conducted in China have shown that residents' social cohesion benefits their metal health, because it encourages them to support each other and exchange health-related information (Chen and Chen, 2015; Wen et al., 2010).

Third, most reviews have recognized psychological stress as the most important pathway linking perception of neighborhood safety to mental health (Lorenc et al., 2012; Won et al., 2016). Some studies have confirmed that perceptions of safety are associated with stress (Chandola, 2001; Hill et al., 2005). However, few have identified the mediating role of stress between perceived safety and mental health. Our results confirm this mediating role. A lack of a sense of safety may decrease an individual's perceived control of the neighborhood living environment and cause psychological stress (De Donder et al., 2013).

Table 3
The association between perception of neighborhood safety and each of four potential mediators.

	Model 2a (DV: physical activities)	Model 2b (DV: stress)	Model 2c (DV: social cohesion)	Model 2d (DV: life satisfaction)
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Fixed part				
Neighborhood safety	0.029** (0.014)	−0.059*** (0.022)	0.036*** (0.013)	0.021*** (0.002)
Male (ref: female)	0.695 (0.361)	−0.078 (0.069)	0.081 (0.053)	0.049 (0.069)
Age	0.097*** (0.013)	0.005** (0.002)	0.003 (0.002)	−0.001 (0.002)
Married (ref. = single, divorced or widowed)	−0.306 (0.340)	−0.025 (0.065)	−0.079 (0.050)	−0.024 (0.065)
Local *hukou* (ref: non-local *hukou*)	0.195 (0.286)	−0.055 (0.054)	0.078* (0.042)	0.032 (0.055)
Education (ref: primary school or below)				
High school	0.399 (0.776)	0.105 (0.148)	0.018 (0.113)	−0.015 (0.148)
College and above	0.639 (0.829)	0.180 (0.158)	−0.020 (0.121)	0.019 (0.158)
Household wealth (ref: Group 1)				
Group 2	0.753 (0.476)	0.025 (0.091)	0.085 (0.069)	−0.229 (0.091)
Group 3	0.990* (0.564)	0.095 (0.107)	0.171** (0.082)	−0.310*** (0.108)
Group 4	−1.081* (0.630)	0.266** (0.120)	−0.111 (0.092)	−0.052 (0.120)
Household size	−0.496*** (0.151)	0.069** (0.029)	−0.006 (0.022)	0.031 (0.029)
Length of residence in the neighborhood	0.007 (0.013)	−0.002 (0.003)	0.002 (0.002)	0.001 (0.003)
Functional restricted (ref: not restricted)	−0.511 (0.614)	0.029 (0.117)	0.138 (0.090)	0.068 (0.117)
Medical insurance (ref: no medical insurance)	−0.870 (0.706)	0.171 (0.134)	0.072 (0.103)	−0.142 (0.135)
Drinking (ref: do not drink)	−0.698* (0.381)	0.131* (0.073)	0.054 (0.056)	−0.123* (0.073)
Smoking (ref: nonsmoker)	0.028 (0.308)	0.016 (0.059)	−0.128 (0.045)	0.138 (0.059)
Constant	1.811 (6.971)	4.054*** (1.116)	1.013 (0.646)	4.853*** (0.787)
Random part				
Var (neighborhoods)	7.592***	0.187***	0.056***	0.081***
Var (individuals)	11.733***	0.425***	0.230***	0.430***
Number of individuals	1029	1029	1029	1029
Number of neighborhoods	35	35	35	35
Log likelihood	−2729.933	−1042.631	−768.275	−1037.743
AIC	5497.868	2123.264	1574.551	2113.488

Note: DV = dependent variable; Coef. = coefficient; SE = standard error; AIC = Akaike information criterion. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Fourth, consistent with previous studies (Leslie and Cerin, 2008), our results show that life satisfaction mediates the relationship between perception of neighborhood safety and mental health. Perception of neighborhood safety has a-long term influence on residents' health-related quality of life, because life satisfaction may decrease when the living environment triggers a sense of fear (Loo, 1986). In China, life satisfaction has been proven to be associated with a sense of safety, especially for migrants who lack social resources and support (Appleton and Song, 2008; Easterlin et al., 2012). The positive effect of life satisfaction on mental health has been widely recognized in China (Feng et al., 2018; Wen et al., 2010). A high level of life satisfaction may be a buffer between stressful life events and mental well-being.

The cross-level interaction effect found in this study suggests that perception of neighborhood safety strengthens the health effects of physical activity and neighborhood social cohesion. Previous studies have confirmed that people with a high level of perception of neighborhood safety are more likely to get fully involved in physical activity (Wendel-Vos et al., 2007; Su et al., 2019; Zhou et al., 2019b), strengthening the health benefits of physical activity. Furthermore, when engaging in physical activity while feeling fearful, the health benefits may be weakened because fear disrupts the levels of some hormones (Roman et al., 2009). The effect of social cohesion on mental health is also strengthened by perceived safety. Residents who perceive their neighborhood as safe are more likely to trust each other, so these residents are more likely to get useful health knowledge and support from their social contacts.

This study has several strengths and limitations. The study makes a methodological contribution to the development of assessments of perceived neighborhood safety. Most studies still rely on questionnaire or traditional field audit methods to evaluate perceived neighborhood safety. These methods are labor-intensive, time-consuming and may be inapplicable to large-scale health research. Even though some researchers have begun to rate perceptions of neighborhood environments based on street view images, the number of rated images is still limited. This study has demonstrated a novel approach to automatically rate images based on a sample of images rated by humans, combining the advantages of traditional field audits, street view data and machine learning techniques. Furthermore, our method is more time- and cost-effective than questionnaire or traditional SSO methods, and can thus be used to assess a large study area. Our method can also objectively compare the results of studies conducted in different cities, whereas it is difficult to compare the results of previous studies that used different human raters.

The following limitations of this study should be noted. First, our research was based on cross-sectional data, so it is difficult to infer causation between perception of neighborhood safety and mental health. Second, some important mediators used in this study (time spent on physical activity and the level of psychological stress) were self-reported. More objective measures of those mediators should be used in future studies. Third, there are different aspects of neighbourhood safety such as traffic-related safety and crime-related safety, but we only focused on general safety in this study. Fourth, street view images are currently unavailable for some cities and some rural areas, so our method may not be applicable for those areas. Fifth, the street views are obtained at one point in time, but perceptions of safety may vary between daytime and nighttime as well as weekdays and weekend. Sixth, we used the images scored by volunteers to represent the perceived safety of local residents, but there may be a mismatch between them. Seventh, perceived safety was not linked to history or contexts of each location, which may lead to the Uncertain Geographic Context Problem (UGCoP) regarding environment-health associations (Kwan, 2012).

5. Conclusions

This study is the first to systematically explore multiple pathways linking perception of neighborhood safety to mental health. In addition, we propose a new approach to assess residents' perceived safety based on street view data and machine learning. The results of multilevel models show that, consistent with previous literature, perception of

Table 4
Physical activity, social cohesion, stress and life satisfaction as mediators of the relationship between perception of neighborhood safety and mental well-being.

	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Fixed part						
Neighborhood safety	0.201** (0.100)	0.201** (0.097)	0.212** (0.102)	0.234** (0.113)	0.156* (0.081)	0.167* (0.095)
Physical activities	0.121*** (0.018)				0.083*** (0.024)	0.083*** (0.024)
Social cohesion		2.084*** (0.164)			1.904*** (0.165)	1.788*** (0.171)
Life satisfaction			0.269** (0.125)		0.245** (0.124)	0.253** (0.125)
Stress				−0.749*** (0.133)	−0.562*** (0.124)	−0.575*** (0.123)
Male (ref: female)	0.701** (0.291)	0.617** (0.273)	0.799*** (0.294)	0.721** (0.289)	0.528** (0.270)	0.719*** (0.268)
Age	−0.017 (0.011)	−0.011 (0.010)	−0.005 (0.01)	−0.002 (0.010)	−0.016 (0.010)	−0.017* (0.010)
Married (ref: single, divorced or widowed)	−0.563** (0.274)	−0.438* (0.257)	−0.615** (0.277)	−0.612** (0.272)	−0.438* (0.254)	−0.479 (0.252)
Local *hukou* (ref: non-local *hukou*)	−0.279 (0.230)	−0.417* (0.216)	−0.239 (0.233)	−0.301 (0.229)	−0.455** (0.214)	−0.474** (0.211)
Education (ref: primary school or below)						
High school	0.249* (0.626)	0.266 (0.587)	0.289 (0.631)	0.364 (0.621)	0.289 (0.578)	0.238 (0.571)
College and above	1.114* (0.668)	1.238** (0.627)	1.188* (0.674)	1.322** (0.664)	1.283** (0.617)	1.197** (0.611)
Household wealth (ref: Group 1)						
Group 2	−0.167 (0.383)	−0.237 (0.360)	−0.132 (0.388)	−0.068 (0.380)	−0.287 (0.355)	−0.290 (0.351)
Group 3	0.009 (0.455)	0.224 (0.427)	0.039 (0.460)	0.176 (0.451)	0.240 (0.423)	0.273 (0.419)
Group 4	0.050 (0.508)	0.074 (0.477)	0.180 (0.512)	0.008 (0.505)	0.277 (0.471)	0.134 (0.466)
Household size	−0.166 (0.122)	−0.211* (0.114)	−0.218* (0.123)	−0.177 (0.121)	−0.131 (0.113)	−0.139 (0.112)
Length of residence in the neighborhood	−0.001 (0.011)	−0.005 (0.010)	−0.001 (0.011)	−0.001 (0.011)	−0.006 (0.010)	−0.003 (0.010)
Functional restricted (ref: not restricted)	−1.502*** (0.495)	−1.841*** (0.464)	−1.537*** (0.499)	−1.523*** (0.491)	−1.744*** (0.458)	−1.830*** (0.454)
Medical insurance (ref: no medical insurance)	−0.009 (0.569)	−0.256 (0.534)	−0.132 (0.574)	−0.045 (0.565)	−0.075 (0.527)	−0.107 (0.521)
Drinking (ref: do not drink)	−0.625** (0.308)	−0.826*** (0.288)	−0.746** (0.310)	−0.621** (0.306)	−0.697** (0.285)	−0.760*** (0.283)
Smoking (ref: nonsmoker)	−0.356 (0.248)	−0.083 (0.234)	−0.321 (0.251)	−0.321 (0.246)	−0.081 (0.231)	−0.093 (0.228)
Neighborhood safety × Physical activity						0.089*** (0.026)
Neighborhood safety × Social cohesion						0.124*** (0.030)
Neighborhood safety × Life satisfaction						0.005 (0.006)
Neighborhood safety × Stress						0.054 (0.036)
Constant	−0.223 (5.039)	−2.035 (4.851)	1.299 (5.181)	3.021 (5.699)	0.504 (5.108)	−0.242 (4.811)
Random part						
Var (neighborhoods)	3.875***	3.610***	4.045***	5.043***	3.950***	3.431***
Var (individuals)	7.619***	6.708***	7.762***	7.504***	6.492***	6.326***
Number of individuals	1029	1029	1029	1029	1029	1029
Number of neighborhoods	35	35	35	35	35	35
Log likelihood	−2507.629	−2443.927	−2514.909	−2499.307	−2422.166	−2407.329
AIC	5055.258	4927.855	5069.818	5038.615	4890.334	4868.66

Note: Coef. = coefficient; SE = standard error; AIC = Akaike information criterion. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

neighborhood safety is positively associated with mental health. Physical activity, social cohesion, stress and life satisfaction mediate this relationship. Our results also suggest that the beneficial effects of physical activity and social cohesion on mental health are strengthened by a perception of neighborhood safety.

Availability of data and material

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Consent for publication

Not applicable.

Conflicts of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Ethics approval and consent to participate

Authorization of the study was consented by Sun Yat-sen University Research ethics committee. All the subjects were informed and consented for the protocol of study.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2019.102186.

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