Landscape and Urban Planning 207 (2021) 104003

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Research Paper

"Perception bias": Deciphering a mismatch between urban crime and perception of safety

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HIGHLIGHTS

- Predicted "Perception of Safety Scores" are significantly associated with reported crime.
- There exists a "Perception Bias" between the perception of safety and reported crimes.
- Intensive daytime activities indicate places "safer than they look".
- More visits at night implies places being "more dangerous than they look".
- Places with more education facilities may have more crimes but still look safe.

ARTICLE INFO

Keywords:
Crime
Human perception
Street view imagery
Urban mobility dynamics
Amenity diversity

ABSTRACT

Crime and perception of safety are two intertwined concepts affecting the quality of life and the economic development of a society. However, few studies have quantitatively examined the difference between the two due to the lack of granular data documenting public perceptions in a given geographic context. Here, by applying a pre-trained scene understanding algorithm, we infer the perception of safety score of streetscapes for census block groups in the city of Houston using a large number of Google Street View images. Then, using this inferred perception of safety, we create "perception bias" categories for each census block group. These categories capture the level of mismatch between people's visually perceived safety and the actual crime rates. This measure provides scalable guidance in deciphering the relationship between the built environment and crime. Finally, we construct a series of models to examine the "perception bias" with static and dynamic urban factors, including socioeconomic features (e.g., unemployment rate and ethnic compositions), urban diversity (e.g., number and diversity of Points of Interest), and urban livelihood (i.e., hourly count of visitors). Analytical and numerical results suggest that the association between characteristics of urban space and "perception bias" over crime could be paradoxical. On the one hand, neighborhoods with a higher volume of day-time visitors appear more likely to be safer than it looks (low crime rate and low safety score). On the other hand, those with a higher volume of night-time visitors are likely to be more dangerous than it looks (high crime rate). The findings add further knowledge to the long-recognized relationship between built environment and crime as well as highlight the perception of safety in cities, which in turn enhances our capacity to design urban management strategies that prevent the emergence of extreme "perception bias".

1. Introduction

There is a growing recognition that a sustainable community should be safe from crime and also perceived by its residents to be safe (Cozens, 2011). Beyond the immediate losses in a crime incident, the fear of crime and the worries over safety often extend the damage of criminal victimization and produce further social consequences at both personal and community levels (Moore and Trojanowicz, 1988). Although

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https://doi.org/10.1016/j.landurbplan.2020.104003
Received 27 April 2020; Received in revised form 18 November 2020; Accepted 21 November 2020
Available online 17 December 2020

people's perception of safety was assumed as more or less a rational response to crime, previous studies show that the trends in levels of fear are not strictly associated with criminal victimization (Skogan, 1986; Fuhrmann et al., 2013; Snyders and Landman, 2018). Moreover, when citizens are asked about the things that frighten them, instead of "real crime" such as theft or robbery, more often there is talk about signs of physical decay and disorder such as "junk and trash in vacant lots, broken windows, bands of teenagers congregating on street corners and other incivilities" (Wilson and Kelling, 1982; Skogan, 1986; Doran and Lees, 2005). The perception of safety, or in other words, a feeling influenced by perceived danger or threat, has a different pattern from criminal victimization across time and space.

Then, how big is the difference between "safe from crime" and "perceived to be safe" in an urban environment? What factors could contribute to the mismatch between the two within cities? A number of studies have attempted to answer these questions by suggesting methods to compare the two concepts. Schweitzer et al. (1999) interviewed residents from 44 neighborhoods in Lansing, Michigan, the United States to obtain local residents' perceptions of crime and compare it with the same neighborhoods' crime rates. More recent works leveraged the development of Geographical Information Science (GIS) to visualize the different spatial pattern of places with high crime rate and clustering of areas that are perceived as unsafe (Fuhrmann et al., 2013; Pánek et al., 2019). These studies present valuable insights into the paradoxical relationship between perception of safety and crimes but also imply challenges to further understand the inherent discrepancy between the two. First of all, much research has loosely used the term "fear of crime" to describe a mix of perceptions (Warr, 2000). "Fear" has been used to indicate personal emotion, perception of environmental risks, or a belief in the likelihood of becoming a crime victim. Second, fear of crime related research mainly relies on methods such as group discussions (Snyders and Landman, 2018) and online questionnaire (Ditton and Farrall, 2017). These methods either do not provide data at a comparable spatial resolution with actual crime data, or are limited to smaller contexts given the cost of the survey process. As a result, there is a lack of empirical analysis on what neighborhood factors, including local socioeconomic characteristics and built environment features, contribute to the potential discrepancy between the crime and people's perception of safety.

To address these challenges, in this paper, we specifically examine one measure of fear aroused by the urban environmental settings. We use the term perception of safety to describe how safe people perceive the immediate physical environment by its appearance, regardless of any victimization experience. More importantly, we focus on interpreting the difference between the actual crime and the perception of safety in a given urban context.

To quantitatively measure people's perception of safety, we employ street view imagery and computer vision techniques. Recently, the development in machine learning algorithms and data collection methods largely improve researchers' capability of describing human perceptions of the built environment. For instance, MIT Media Lab built a dataset containing millions of online volunteers' perceptual ratings on more than 100,000 Google Street View images worldwide (Naik et al., 2014). Based on this massive crowd-sourced dataset, researchers train models built on scene understanding algorithms in computer vision, and in turn, produce predicted scores of the perceived level of safety, wealth, liveliness or depression in any given geography context (Dubey et al., 2016; Zhang et al., 2018). These studies embrace the fact that seeing is a process in which environmental stimuli are organized into our purposive organism, and human beings' feeling of safety or danger exists when memory and anticipation are able to wield sensory impacts into the personal experience (Tuan, 1977).

Following these efforts, this paper analyzes the reported crime and other geo-referenced data in the city of Houston to estimate a "perception bias," the mismatch between people's perception of safety and actual crime. Here we ask three main questions: 1) How much the perception of safety can explain the variation of crimes? 2) How to quantitatively measure the current "perception bias" at the census block group level? 3) What neighborhood characteristics contribute to the current "perception bias"?

The rest of the paper is organized as the following structure. Section 2 reviews previous work on crime, perception of crime and cities. Section 3 introduces the data sources we use in the analysis. Section 4 explains the methodology. Section 5 presents the results showing what neighborhood characters determine the "perception bias." Section 6 and 7 discuss our study results and presents paths for future studies.

2. Literature review

2.1. Crime and cities

Criminologists, social observers, and planners have studied the intricate relationship between crime, fear of crime, and cities since the early 1920s (Shaw, 1929). Jane Jacobs's work (Jacobs, 1961) described the relationships between street layouts, diverse mix of land use and crime. She argued that a mixed-use neighborhood with residential, commercial, institutional and leisure would be safer than single functional areas as these areas ensure informal surveillance: "eyes on the streets." Jeffery (1971) first brought up the phrase crime prevention through environmental design (CPTED). This strategy is currently applied in many cities such as London and Sydney (Cozens, 2011). In 1972, Oscar Newman's (Newman, 1972) defensible space started to influence a generation of planners: he argued that poor design elements decrease residents' willingness to use and defend local space. Spatial settings such as fences and hedges can be regarded as physical barriers, and porches and mailboxes at the street can be regarded as physical configurations that increase surveillance. Growing out of these early literature, more recent studies in environmental criminology state that spatial distribution of offenses and offenders throughout the city is not random (Cozens, 2011; Eck et al., 2007; Kinney et al., 2008). With the increasing availability of crime report data, theoretically grounded empirical analyses of spatial theories of crimes show that neighborhood social features, including poverty, unemployment, and ethnic compositions, have high explanatory power of crime occurrence (Harries, 1995; Cahill and Mulligan, 2007). Besides, some physical features, such as commercial centers, sports facilities, and transportation stations, often play as crime attractors (Brantingham and Brantingham, 1995; Anderson, 2007).

2.2. Perception of safety and cities

In parallel with the studies of actual crime occurrences and cities, people's perception of safety in cities also have received extensive attentions since the 1960s (Furstenberg, 1971; McIntyre, 1967). Surveys and qualitative studies have confirmed that physical environments that are dark, lonely, unattractive, or uncared-for stimulate people's fear (Warr, 1990; Vrij and and Winkel, 1991; Doran and Lees, 2005). More recently, researchers have leveraged the GIS to investigate the "spatial specific" aspects of fear of crime at a finer scale in cities (Liu and Eck, 2008). Doran and Burgess (2011) advocate the importance of crime-related fear mapping to provide an additional layer of understanding people's "spatial choices." Solymosi et al. (2015) used a mobile app to map people's experience of fear at different places throughout the day. Song et al. (2020) discussed the differences between property and personal safety perceptions that affected international migrants in China. In practice, police also use environmental audits, a process identifying conditions that are indicative of crime, disorder, and other threats to safety to remove sources of fear (Cordner, 2016).

Compared to the collection of actual crime records, collecting data on people's perception of safety and fear of crime do not yet have a standard process. The General Social Survey (GSS) has been asking the question "Is there any area right around here – that is, within a mile –

where you would be afraid to walk alone at night?" to examine respondents' fear of crime. In a similar fashion, the National Crime Survey (NCS) has been routinely surveying people by asking "How safe do you feel or would you feel being out alone in your neighborhood at night?" since 1973. These surveys have been conducted at a national scale on an annual routine, but do not offer neighborhood-level insight. Individual researchers have designed more specific surveys to collect "spatial specific" data to understand the fear of crime (Pánek et al., 2019; Fuhrmann et al., 2013; Kohm, 2009). Schweitzer et al. (1999) interviewed residents from 44 neighborhoods in Lansing, Michigan, the United States to obtain local residents' perceptions of crime and compare it with the same neighborhoods' crime rates. They found that grocery stores' presence was related to both crime and perception of crimes, which contradicts Jane Jacobs' diverse land-use statement. Snyders and Landman (2018) conducted a focus group discussion in two neighborhoods with high numbers of crimes in South Africa. They found that most community members do not display high levels of fear despite the local high crime rates. Pánek et al. (2019) used an online map-based questionnaire to collect people's perception of crime and compare the response with local recorded crime data through map visualizations in Ostrava, Czech Republic. Fuhrmann et al. (2013) conducted a mapping analysis comparing university crime statistics with students' perceptions of crime. Their results also indicate a spatial discrepancy between fear and crime, especially on harassment and sexual assaults.

These studies mainly rely on various types of surveys (Henson and Reyns, 2015), which either do not provide data at a comparable spatial resolution with actual crime data, or are limited to smaller contexts given the cost of the survey process. In addition, the amount of time it consumes to conduct individual interviews usually prohibits the researchers from expanding the study to a city or regional scale quickly. To circumvent these limitations, this work introduces a new approach to measure people's perception of crime using computer vision and further quantify the discrepancy between crime and perceptions.

3. Methodology

3.1. Study area and data

3.1.1. Study area

This research focuses on one of the major cities in the U.S., Houston, Texas. Houston has a population of approximately 2,320,268, and it is the most populous city in the state of Texas. The city was selected for this study both for its higher crime rate compared to other U.S. major cities and its past efforts in curating a sense of safety among its residents. According to the FBI's 2018 Uniform Crime Reporting Program, Houston's violent crime rate of 10.26 per 1000 population is more than double the comparable national rate. Local government agencies and community organizations have launched many programs to prevent crimes since the 1980s. Recent programs include the "Keep Houston SAFE" (https://www.houstontx.gov/) campaign developed by the Houston Police Department and Safe Community Program launched by Crime Stoppers of Houston to prevent crime events and forge safer communities. Our empirical analysis includes a total of 1132 census block groups within the I-610 freeway in the city of Houston.

3.1.2. Perception measurement from Google Street View images

Google Street View (GSV) is a map service providing visual information of streets in more than 100 countries in the world. We take GSV images as the proxy of the physical streetscapes of Houston and predict people's "visual perceived safety" of images using a pre-trained deep learning model. To access images, we first generate sampling points along the road network of Houston with a 50-meter interval. Secondly, we request the GSV images based on the sampling points through GSV Application Protocol Interface (API); for each location, four images of different directions of view along the road are obtained to describe the panoramic view of streetscapes. In total, we collected 384,180 GSV images from 96,045 locations in Houston, with most of the images taken between 2015 through 2017.

To simulate people's perception of safety on the streets of Houston, we employ a pre-trained deep learning model to predict safety scores of street view images of the city (Zhang et al., 2018). The model is trained with a crowd-sourced dataset, Place Pulse, collected by MIT Media Lab, which contains millions of ratings on around 110,000 street view images from all over the world (Naik et al., 2014). For each trial, an online participant is asked to click one of two street view images on a webpage, in response to questions like: "which place looks safer". Since its launch in 2007, more than 80,000 online volunteers worldwide contributed over one million pairwise comparisons within nearly ten years (Dubey et al., 2016). More importantly, the image diversity and rating consistency have been evaluated by previous works (Naik et al., 2014; Dubey et al., 2016), showing no significant cultural bias in the dataset, which demonstrates its representativeness and generalizability. Here, we consider this Place Pulse dataset as knowledge of human's general visual perceptual preferences on urban appearance. A deep learning model can be trained accordingly by prior knowledge as such to learn how common individuals evaluate an urban streetscape. In this work, we adopt the ResNet-50 model trained in Zhang et al. (2018) to predict the 384,180 GSV images of Houston. Each census block group contains 317 images on average. The largest census block group contains 960 images. We exclude the census block groups that contain fewer than 10 images. For each image, the model yields a safety score ranging from 0 to 10. The score of each census block group is then calculated by averaging scores of all the images in the block group. Fig. 1 shows the spatial distribution of "perception of safety" of Houston and there is a clear spatial pattern indicating where the "safest" place is. Generally, the downtown areas look less safe than most of the other places and western areas look safer than eastern ones. To clarify the concept, by "perception of safety" we mean the general individual's visual perception on a street scene, without any personal experience related to the context.

Fig. 2 shows the GSV images that contain similar elements but are predicted with different safety scores. Row A includes images with high safety scores, and row B includes images with low safety scores. We observe litter, overgrown vegetation, broken pieces of road, and scattered trash cans in row B, these elements coincide with the evidence of physical disorder (Toet and van Schaik, 2012). In row A, we observe more elements that correspond to the concept of "cues to care" (Troy et al., 2016; Brown and Bentley, 1993), such as clean streets, well pruned vegetation, new construction, and well-maintained residential yard.

3.1.3. Reported crime

The data measuring criminal activity within the study area come from the Houston Police Department (HPD) National Incident-Based Reporting System (NIBRS) Data. Information provided includes the crime offense type, the date and year when the crime was committed, and its geographic location (street name and block range). These data provide a rich assessment of criminal activity in Houston that is spatially referenced. However, the use of such data does have some caveats. The crime information only represents police services where a report was made and thus does not include other criminal activities that were not reported. Additionally, HPD completed the transition from UCR to NIBRS classification of crime in 2018. From January 2018 to May 2018, the crime offense types were classified according to UCR Traditional Summary Reporting. After June 2018, crimes records were classified based on NIBRS standard. To measure a full year criminal activity in 2018 by different crime types, we matched the different crime types between UCR and NIBRS per report by Rantala (2000). Moreover, we acknowledge that the year of crime data does not conform strictly with the GSV data (2015–2017). This study takes the assumption that built environment does not have significant changes from year 2017 to 2018. Lastly, geocoding the point location of reported crimes from street name and block range provide potential for error. The imported data must

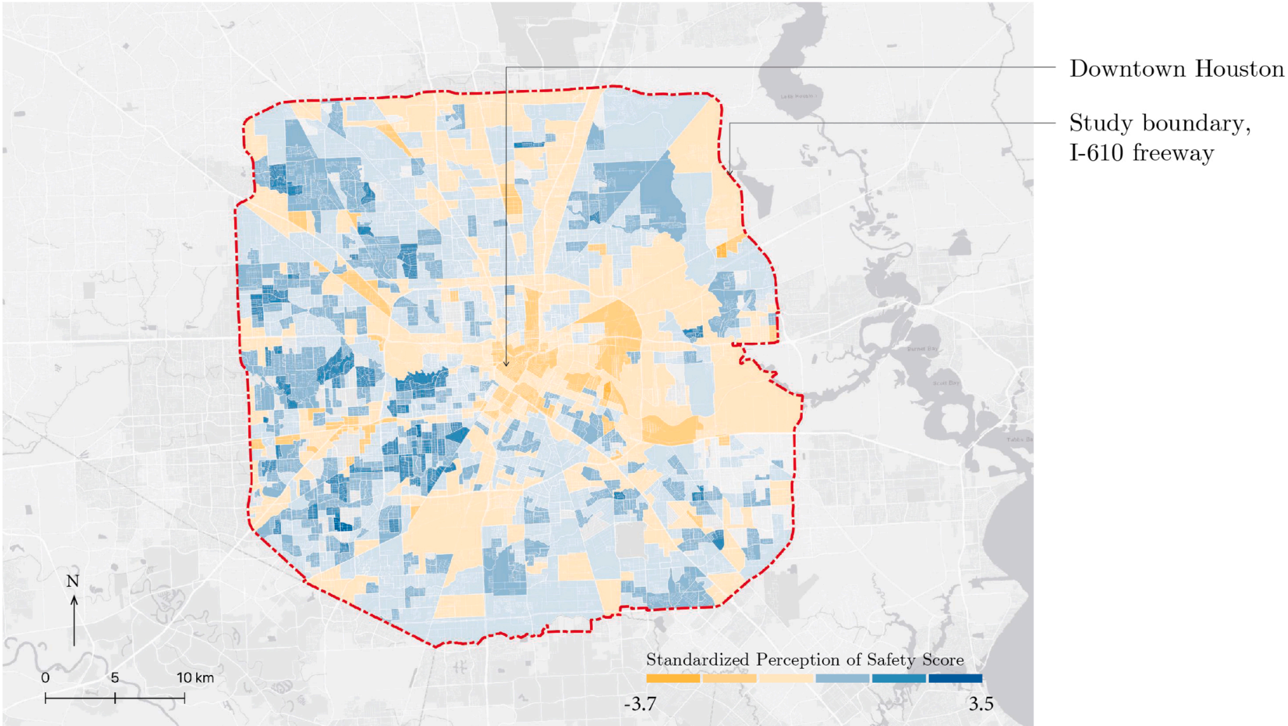

Fig. 1. "Perception of Safety Map" of Houston at census block group level. Values shown in dark yellow depict areas with the lowest safety scores, whereas dark blue areas indicate the highest safety score.

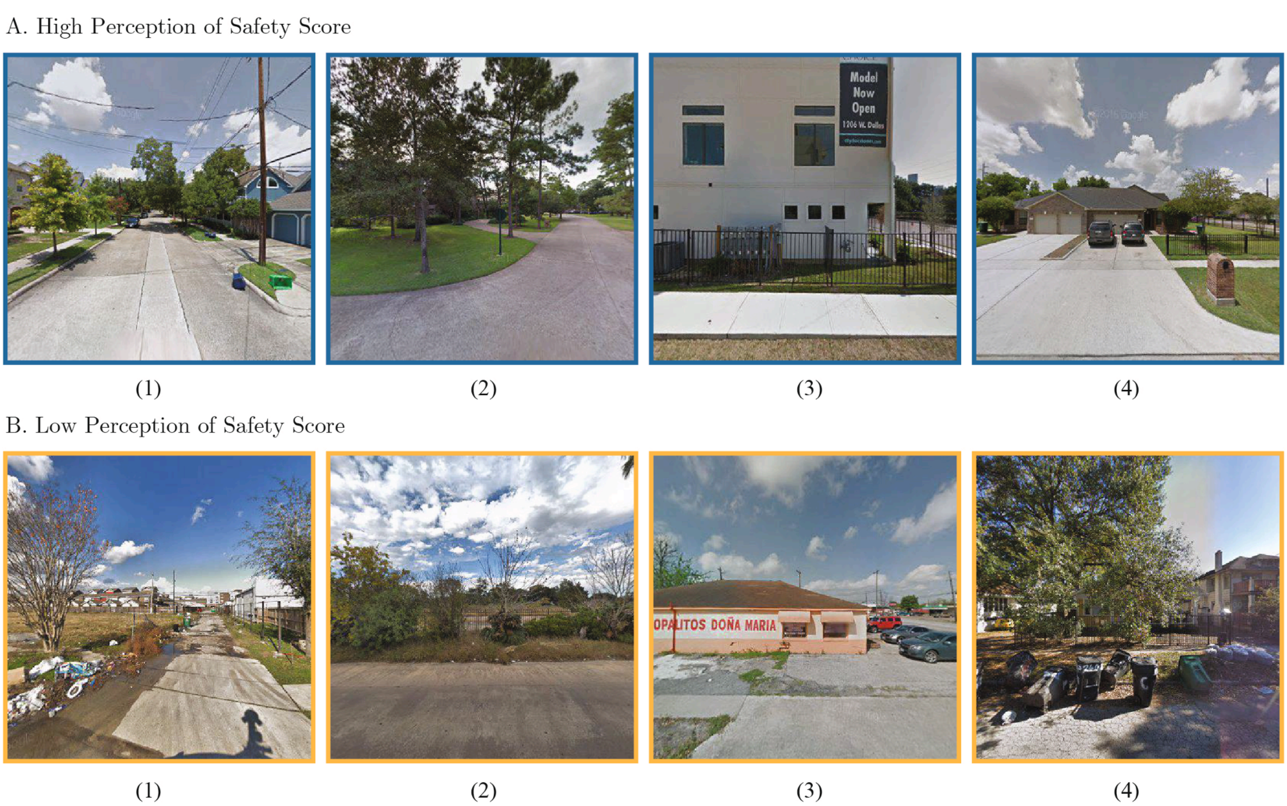

Fig. 2. Image samples from the GSV images dataset. The first row (A) shows images with high safety scores. The second row (B) presents images with low safety scores.

have standardized street address to be geocoded, thus particular addresses interpreted from block range and street name may not be mapped through geocoding procedures. Our geocoding procedure used in this paper produces 92.7% success rates for all crime incidents reported in year 2018 (101,725 out of 109,620 crime incidents). With a high success rate of matches and the nature of the address records, the analysis in this study is performed without concern for bias (Ratcliffe, 2004). After geocoding process, we further aggregate the count of crime incidents by their associated census block groups. The geocoding process and data aggregation are performed with python geopandas and shapely packages.

In the following research, we study crime-related safety by grouping crimes into two broad classifications: 1) violent crimes: according to the National Institute of Justice's definition, we group murder, robbery, rape, and aggravated assault into violent crimes; 2) other crimes: consisting of burglary, automotive theft and theft. Though violent crimes have broader categories than other crimes, the two categories are used to indicate different targets of crime: the person and property (Anderson, 2007). The total dataset includes 17,104 reported violent crimes and 56,371 other crimes for all census block groups in our study area.

Fig. 3 maps the spatial distribution of violent crime per thousand residents and other crime per thousand residents in each census block group. The values are logarithmically transformed for ease of interpretation and stabilization of the variance. Values shown in darker red depict areas with a higher crime rate, and areas in darker blue indicate a lower crime rate. This figure indicates that crimes of all types cluster towards the city center, where activity intensity is the highest. This pattern makes sense as the previous study shows that the higher intensity of urban life lower the probability of arrest and a lower likelihood of recognition (Glaeser and Sacerdote, 1999). On the other hand, the distribution of violent crime rate appears relatively more dispersed compared to other crimes.

3.1.4. Urban livelihood: hourly number of visitors

The visitor patterns of all census block groups in the study area are retrieved from the SafeGraph mobile phone dataset. SafeGraph aggregates anonymized location data from mobile user applications to the census block group level. For each census block group, the hourly number of visitors is calculated from October 1st to October 30th, 2018. The time of the visitor pattern data is not precisely consistent with crime data, with a gap being less than 12 months. We assume human activity patterns of a city are relatively stable for this short period given that no drastic changes in land uses–the main driving force of human activity–are observed during this time period.

To incorporate the human mobility dynamics in this empirical study, we create a correlation matrix between visitor counts for every hour during the day to select the representative hours for daytime and nighttime populations. We use visitor counts at 6 pm as a proxy representing the daytime population, and 2 am to represent the nighttime population for this study. This is because that visitor volumes at 6 pm and 2 or 3 am are the least correlated throughout the day (see Fig. 4).

3.1.5. Urban diversity: density and diversity of points of interest (POIs)

To measure each census block group's functional identity, we include Points of Interest (POIs) Data from SafeGraph. Safegraph's POI dataset contains the names, geographic coordinates, and category code following the North American Industry Classification System (NAICS) for 12 types of business and service amenities in our study area. We extract from the dataset of amenities that belong to the categories of retails, education facilities, information services, public administrations, car repairs, accommodations, arts, finance organizations, manufactures, and wholesalers. To count the number of amenities in each census block group, we assign each POI to the census block group boundary within which it falls.

In this study, we are particularly interested in the density and diversity of POIs and how they relate to crime and perception of safety. Here, we define the density of POIs as $p = N/S$, where N indicates the number of POIs in a given census block group and S is the area of the census block group. We describe the diversity of POI by calculating a diversity index as the entropy among ten types of POIs:

$$Diversity_{x,i} = -\sum_{i=1}^{n}(P(x_i)log(P(x_i)) \tag{1}$$

where x_i represents one type of POI, which occurs in each census block

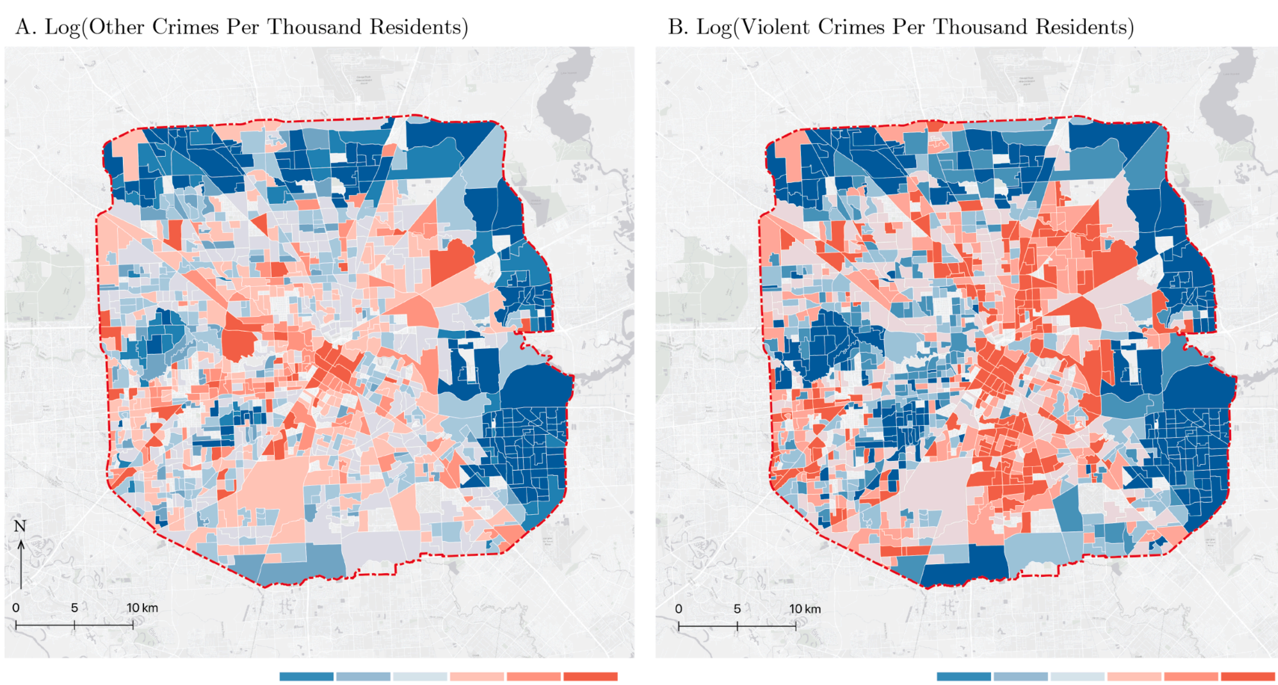

Fig. 3. Geographical distribution of number of violent crimes (right) per thousand residents and number of all other crimes per thousand residents (left) in each census block group. The values are logarithmically transformed. The map was created by QGIS 3.4 (same for the maps below).

group with probability $P(x_i)$. Here $P(x_i) = N_x / N_{total}$, representing the proportion of POI type x in comparison to the total count of all POIs in census block group i.

3.1.6. Socioeconomic features

We extract socioeconomic features at census block group level from the American Community Survey (ACS) 5-year Estimates in 2018. In particular, the data in this research includes information about population, ethnicity, and unemployment rate. The selection of these variables is based on a stream of literature that found a high concentration of crime is related to economic disadvantage and a high degree of ethnic heterogeneity (Sampson et al., 1997; Cahill and Mulligan, 2007). In particular, we describe the economic disadvantage using the unemployment rate. For the racial composition, we exclude any ethnic-specific variables (e.g., percentage of black people) to avoid ethnic-specific bias. Instead, we use ethnic diversity index computed as the Hirschman–Herfindahl index of six population groups: white, non–Hispanic black, Hispanic, Native American, Asian, and others (De Nadai et al., 2020). The index is defined as $H = 1 - \sum_{i=1}^{N}(s_i^2)$, where s_i is the proportion of people belonging to the racial group i, and N is the number of racial groups included in our study. Most of the parameters used in this study have a coefficient of variation (CV) between 12 to 40, with the exception of black population (40). We circumvent this limitation by excluding individual ethnic-specific variables.

All the above mentioned data pre-processing are conducted with Python 3.6.

3.2. Research framework

To shed light upon a diverse set of factors at play with the level of "perception bias" in the city, we design a research framework, as shown in Fig. 5. First, we start by studying the connection between the perception of safety and the variation of reported crime at the census block group level in Houston. Second, to describe the discrepancy between the two concepts, we construct the category of "perception bias" by comparing the crime victimization rate and the predicted perception of safety score. Finally, to explore how urban characteristics are related to "perception bias," we studied three major types of urban features:

- "Socioeconomic" including population, ethnic diversity and economic disadvantage;
- "Urban livelihood" measured by aggregated and anonymized human mobility data;
- "Urban Diversity" described by the number and variety of points of interest (POIs) in each census block group.

3.2.1. Explain crime with safety score

We start our study by looking at the correlation between the perceptions of safety and actual reported crimes in Houston. The intention of this experiment is two-folded: one is to test the generality of the deep learning model and validate the information contained in the safety score produced by the model; the other is to uncover how much the current perception of safety can explain the variation of reported crime occurrence. Research on geographical distribution of crimes usually measures crime in crime counts and crime rate. To avoid potential impacts on our analysis brought by different measures, we include both crime counts and crime rates as our dependent variables in this section.

Due to the presence of spatial auto-correlation in our dataset, the standard assumption in an ordinary least squares regression of independent errors is violated. Previous studies have shown that crimes are not randomly distributed across space (Cozens, 2011; Eck et al., 2007; Kinney et al., 2008), but rather concentrated in areas – there could exist spillover effects of crime occurrence among adjacent neighborhoods. Therefore, we use a spatial lag regression model to account for these spatial dependencies. We decompose the error term of the a ordinary least square model (Eq. 2) into a spatially lagged dependent variable term and an independent error term, as Eq. 3 shows:

$$log(Crime\ Rate_i) = \beta_0 + \beta X_i + \eta Perception\ Safety_i + \epsilon_i \quad (2)$$

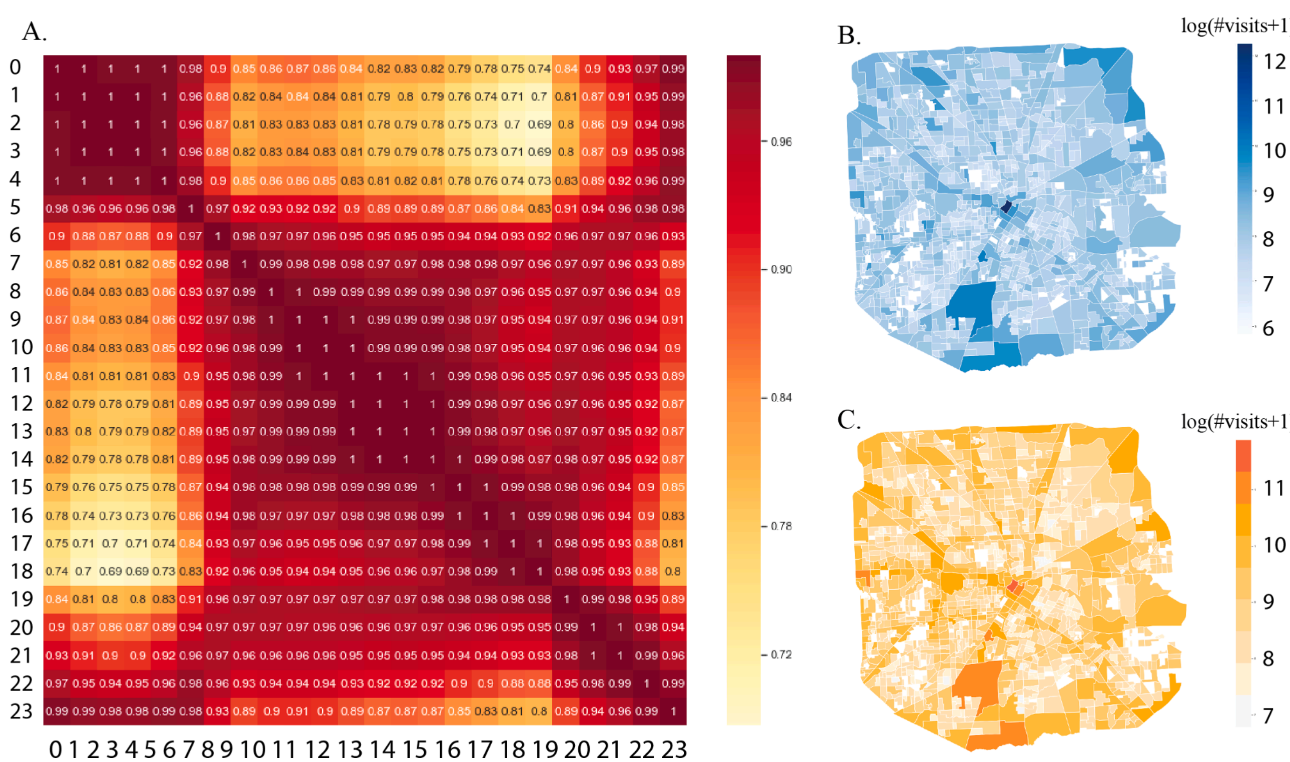

Fig. 4. A) Shows correlation matrix colored according to the correlation coefficient value. B) Maps the geographical distribution of visiting volumes at 2 am; C) maps the geographical distribution of visiting volumes at 6 pm.

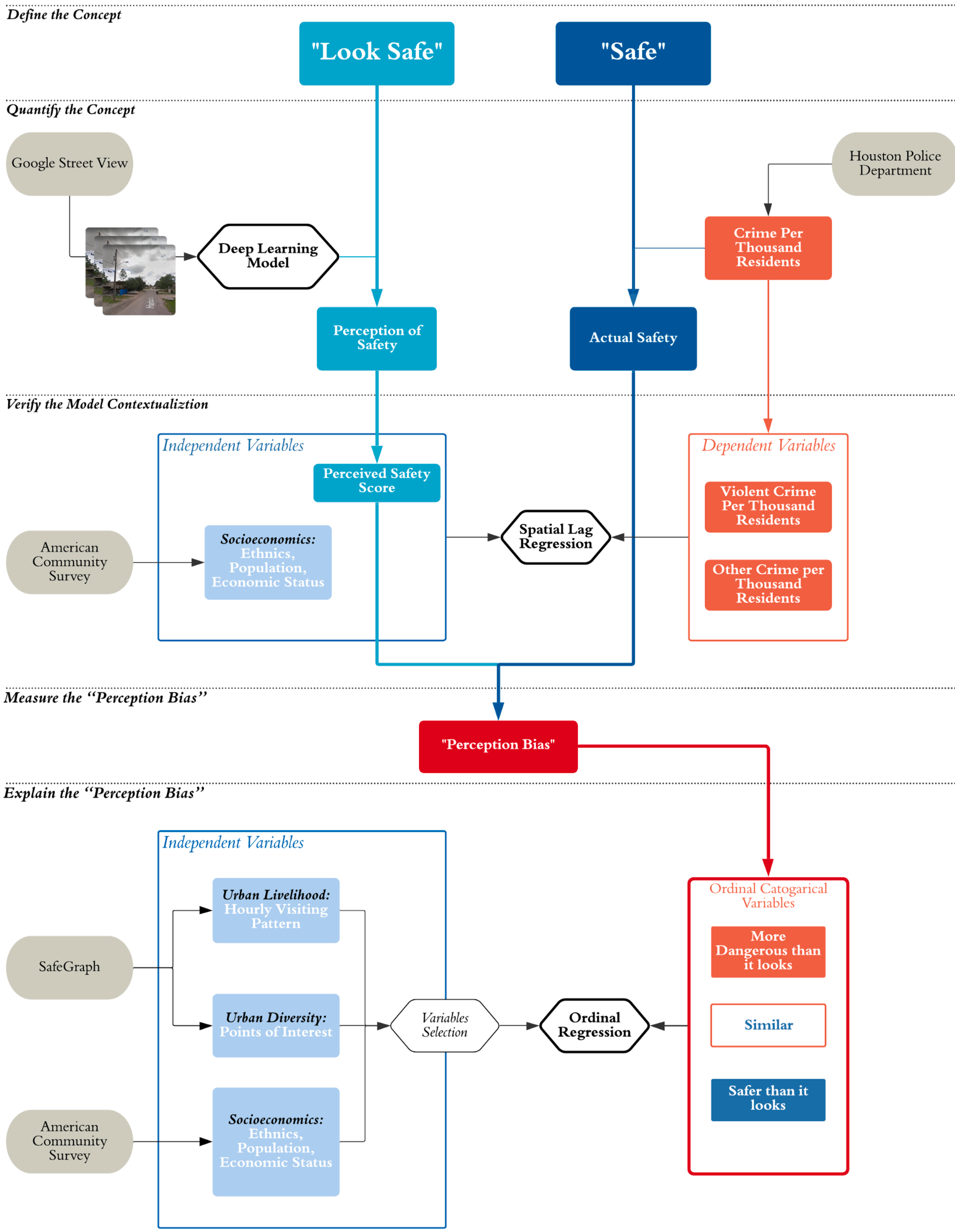

Fig. 5. Overall Research Design. Our research consists of five main parts: 1) Define the concept; 2) Quantify the concept; 3) Verify the deep learning model's contextualization; 4) Construct the dependent variables: Measure the "Perception Bias"; 5) Construct the empirical study: Explain the"Perception Bias.".

$$log(Crime\ Rate_i) = \beta_0 + \beta X_i + \eta Perception\ Safety_i + \rho \sum_j w_{ij} log(Crime\ Rate_i) + \epsilon_i \quad (3)$$

In the dependent variable term in Eq. 3, ρ is the estimated coefficient of a census block group i's neighboring census block groups, w_{ij} denotes the spatially lagged $log(Crime\ Count)$ and $log(Crime\ Per\ Thousand\ Residents)$ at census block group i.

The spatial weights matrix used in this analysis is measured with Queens' contiguity, meaning that all census block groups sharing a boundary in any direction form the census block group in question are considered contiguous. If two census block groups (i and j) share at least one boundary, the contiguity weight is 1, 0 otherwise. We use row-normalized weights in our model. Given that spatial lag regressions do not have actual R^2, we calculate a $pseudo-R^2$ to assess the models' goodness of fit.

3.2.2. Measure the "perception bias"

To explain the discrepancy between the "perceived level of safety" and the "real level of safety," we construct the "perception bias" with three ordinal categories: 1) "More dangerous than it looks": crime occurs at a high rate (above the 50th percentile), but the predicted perception safety scores of local street views are high (above the 50th percentile); 2) "Similar": crime rate is high and perception safety is low or crime rate is low and safety perception is high. 3) "Safer than it looks": crime occurs at a low rate (below the 50th percentile), but the predicted perception safety scores of local street views are low (below the 50th percentile).

Fig. 6A, B) illustrate the method of aggregating all census block groups into three categories by comparing their safety perception score and crime rates. Fig. 6C, D) map the spatial distribution of this "perception bias" in our study area. Values shown in red are areas of high crime rate but also high predicted safety scores (*more dangerous than it looks*) and areas in dark blue depict areas with low crime rate but also low safety scores (*safer than it looks*). The light blue areas indicate a smaller difference between the predicted safety scores and the actual crime rate. Although in Fig. 3 we learn that census block groups with high crime rate tend to cluster towards the city center, three maps in Fig. 6 show that these census block groups around the city center tend to have more consistency between perception of safety and crime rates. Overall, we show that areas of "perception bias" are widely dispersed throughout the study area.

3.2.3. Explain the "perception bias"

We design an ordinal regression model with a spatial conditional autoregressive (CAR) structure (Goodchild and Haining, 2004) to further explore more systematically the factors contributing to the observed perception bias. Prior studies have shown socioeconomic features, urban environment features and human mobility all have connection with crimes as well as how people perceive risks in cities. However, there also exists conflicting voices particularly between criminology studies and urban planning theories. High densities and mixed-use development are generally accepted by planning literature as critical features of sustainable urban environments (Jacobs, 1961;

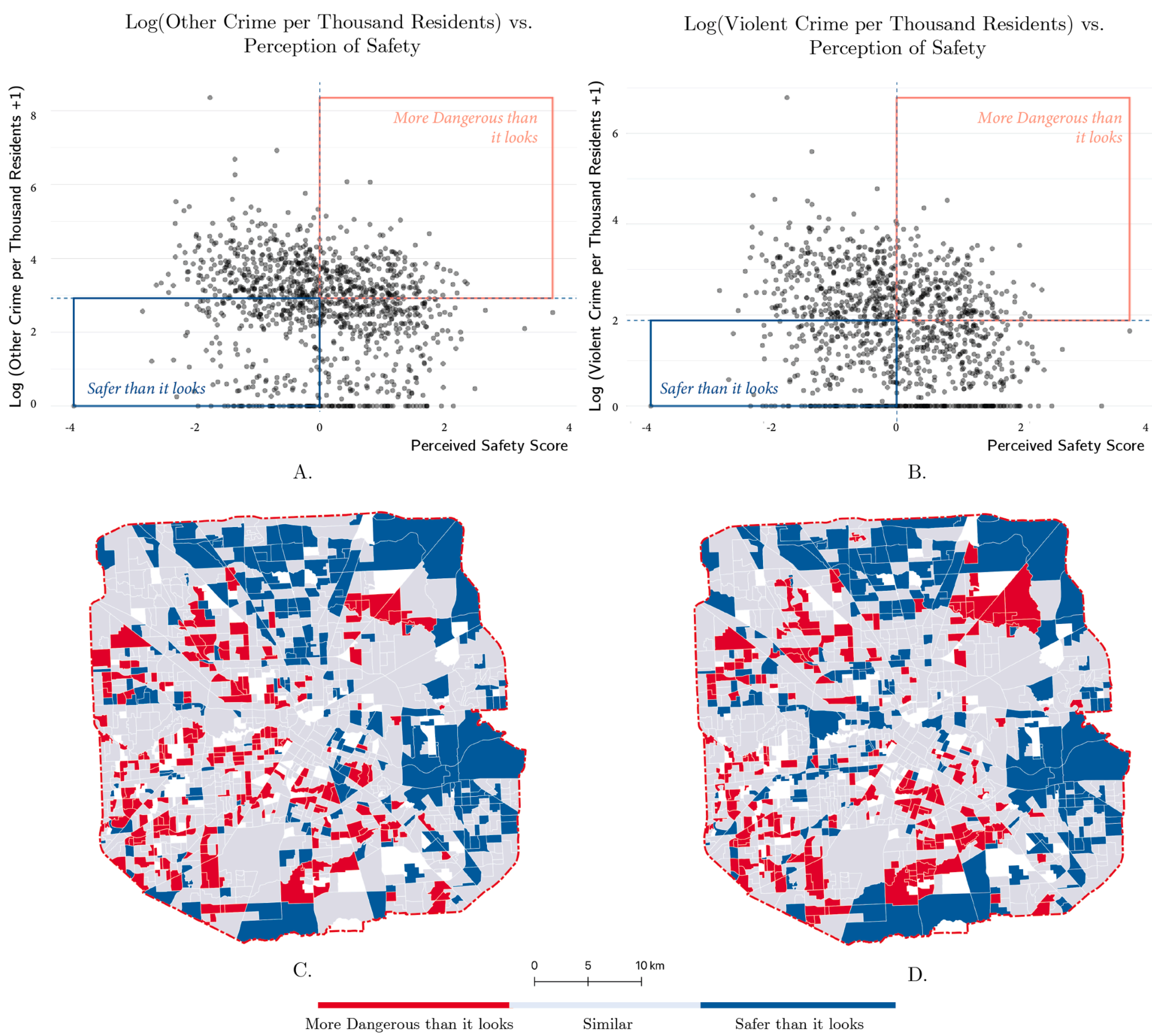

Fig. 6. A and B: Establish categorical variables by dividing the data into three categories. C and D: Geographical distribution of the "perception bias" in the study area.

Grant, 2002), whereas some works claim that mixed-use development and high density are not always desirable and also "not totally benign" (regarding crime events) (Kitchen and Schneider, 2007). Inspired by these arguments, in our study, three types of urban characteristics are included in the ordinal regression for explaining the "perception bias." They are: 1) "social features" indicating local demographic and socioeconomic data; 2) "urban vibrancy" measured by aggregated and anonymized human behavioral data derived from mobile network activity at different hours of the day; 3) "urban diversity" described by number and variety of POIs in each census block group.

We represent three "perception bias" categories with a vector $y = [y_1, y_2, y_3]$, where:

$y_1 = 1$ represents "More dangerous than it looks" block groups, 0 otherwise.

$y_2 = 1$ depicts block groups of the "Similar" perception bias category, 0 otherwise.

$y_3 = 1$ indicates "Safer than it looks" block groups, 0 otherwise.

To analyze the role of different factors in explaining the "perception bias," we estimate the following spatial auto-regressive ordinal logistic regression models,

$$Logit(P(Y \leqslant y_j)_i) = \alpha - \beta A_i - \theta V_i - \gamma X_i - \sigma WY - \epsilon_j \tag{4}$$

where the $P(Y \leqslant y_j)_i$ is the cumulative probability of a census block group i less than or equal to a specific category in "perception bias," where $j = 1, 2, 3$. $Logit(P(Y \leqslant y_j))_i$ is the log odds of census block group i being less than or equal to a category. X_i is a vector that captures the neighborhood "socioeonomic" features including population, unemployment rate and ethnic diversity for census block group i. V_i describes the "urban livelihood," recorded visit pattern at daytime and nighttime of census block group i. A_i represents the "urban diversity" described by the variety and density of public and private amenities. W_i is a binary spatial weights matrix identifying whether a census block group i shares a border with census block group j, and σWY is the spatial lags of the dependent variable Y (ordinal category of "perception bias"). $\beta, \theta, \gamma, \sigma$ are the parameters to be estimated and α is the intercept. All estimation is performed using the *brms* (Bürkner, 2017) package in R 3.6.3. Analysis was performed with all parameters transformed by subtracting their mean and divided by their standard deviation.

4. Results

4.1. How much the perception of safety can explain the variation of crime rates?

Columns 1, 3, 5, and 7 in Table 1 present our models by regressing socioeconomic features of each census block group on crime. These four models retain population, population density, ethnic diversity, and unemployment rate. With total population controlled, areas with higher population density have reduced the level of non-violent crimes, consistent with the presence of guardianship and concept of "eyes on streets" discussed in the introduction. The higher unemployment rate is associated with more violent crimes, and a more diverse racial composition also connects with more crimes. These results resonate with the works in social disorganization theory that high degrees of ethnic heterogeneity and social/economic deprivation are expected to have positive relationships with crime (Cahill and Mulligan, 2007; Anderson, 2007). Therefore, these four models set up a reference in the study.

Columns 2, 4, 6, and 8 report the results, including standardized safety score. All four sets of models indicate a significant correlation between the perception of safety and different measures of crimes in Houston. The estimates in columns 1, 2, 5, and 6 show that one standard deviation increase of the perception of safety is associated with a 13.5% decrease in violent crime count and a 13.2% decrease in number of violent crimes per thousand residents. Columns 3, 4, 7, and 8 imply that one standard deviation increase of the perception of safety is associated with an 8.7% decrease in other crime count and a 12.4% decrease in number of other crimes per thousand residents.

In addition, by comparing the four pairs of models, columns 2, 4, 6, and 8 all report an improved *pseudo* $-R^2$ in comparison to columns 1, 3, 5, and 7. This result implies that by adding perception of safety to the models, we improve the models' fit with the data. Moreover, models using crime per thousand residents as dependent variables show smaller AIC and better *pseudo* $-R^2$. Therefore, in the following section, we continue to use number of reported crimes per thousand residents as the measure of crime to construct the "perception bias".

Through the preliminary analysis between crime and perception of safety, we identify significant correlations between the two and a level of mismatch. By including the safety score into all four sets of models, we are able to explain around 50 percent of Houston's crime variation,

Table 1
Explain crime rate with perception of safety using spatial lag regression.

	Dependent variable							
	Log (Violent Crime)		Log (Other Crime)		Log (Violent Crime per Thousand Residents)		Log (Other Crime per Thousand Residents)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Population (thousand)	0.066*** (0.026)	0.065*** (0.026)	0.115*** (0.029)	0.115*** (0.029)	−0.169*** (0.023)	−0.171*** (0.023)	−0.169*** (0.026)	−0.170*** (0.026)
Population Density	−0.006 (0.004)	−0.004 (0.004)	−0.021*** (0.005)	−0.019*** (0.005)	−0.019*** (0.004)	−0.012*** (0.004)	−0.029*** (0.004)	−0.026*** (0.004)
%Unemployment	0.012*** (0.004)	0.012*** (0.004)	−0.002 (0.004)	−0.003 (0.004)	0.013*** (0.004)	0.012*** (0.003)	−0.001 (0.004)	−0.002 (0.004)
Ethnic Diversity Index	0.919*** (0.145)	0.894*** (0.143)	0.967*** (0.159)	0.930*** (0.132)	0.874*** (0.129)	0.852*** (0.127)	0.973*** (0.145)	0.940*** (0.143)
Perception of Safety		−0.135*** (0.025)		−0.132*** (0.028)		−0.087*** (0.023)		−0.124*** (0.025)
Observation	1158	1158	1158	1158	1156	1156	1156	1156
AIC	3041	3014	3288.7	3267.8	2774.1	2744.5	3068.1	3046.1
AIC Linear Regression	3632.7	3581.5	4004.6	3978.3	33355.4	3294.6	3782.5	3750.8
Pseudo-R^2	0.4703	0.4834	0.5086	0.5183	0.4862	0.5007	0.5291	0.5388
Moran's I	−0.0497	−0.0484	−0.0467	-0.0452	−0.0606	−0.0579	-0.0597	-0.0564
Moran's I p-value	0.9972	0.9965	0.9954	0.9941	0.9996	0.9994	0.9996	0.9992

Note: This table reports the spatial lag regression coefficients of perceived safety. All six models' Moran's I have p-value larger than 0.1, indicating little autocorrelations among the residuals in each model. Here we use standardized "safety score" for all models. We report AIC in comparison to Linear Regression AIC to show model fit.

* * * denotes a coefficient significant at the 1% level, ** at the 5% level, and * at the 10% level.

leaving a proportion unexplained. We also observe the difference between the spatial distribution of crime and the perception of safety by comparing Figs. 1 and 3. These observations are on par with the previous studies done by Pánek et al. (2019) and Snyders and Landman (2018) – areas that make people feel unsafe do not necessarily have high crime records. This intertwined connection between perception of safety and the actual victimization rate indicates a “perception bias.”.

4.2. What neighborhood characteristics contribute to the current “perception bias”

In Section 3.2.2, we have presented how to measure the discrepancy between the perception of safety and the “actual level of safety” by constructing a “perception bias” variable. Here, we discuss our empirical results in deciphering what urban characteristics contribute to this “perception bias”.

Table 2 reports the ordinal logistic regression results of Eq. 4. Each row reports the coefficients of the neighborhood characteristics on “perception bias”. Columns 1, 2, and 3 present “perception bias” measured with violent crime. Columns 4, 5, and 6 present “perception bias” measured with other crimes. Fig. 7 illustrates the strength of coefficients and significance of each parameter for the final model.

Columns 1 and 4 show the result on our baseline models that only include each census block group’s social features. Although population, population density, ethnic diversity, and economic status all show strong connections with crimes in our previous model, we found that they exhibit different strengths in estimating “perception bias” by crime type. Conditioning on the residential population, places with high population densities have a negative relationship with the “perception bias” defined by violent crime. But this association vanishes when we include the dynamic visitor patterns and the density of POIs in column 3. Areas with high percentages of unemployment tend to have a higher crime rate than their local safety scores indicate, implying that the unemployment rate might not fully represent themselves through the built environment appearance. Still, it has a strong connection with crimes.

Columns 2 and 5 report that increased counts of visitors during the day and night have inverse relationships with the “perception bias,” respectively. Areas with a high volume of visitors during the night tend to have higher crime rates than their perception of safety scores indicate. In contrast, a higher number of visitors during the day is more associated with areas that are safer than they look.

Areas with dense and mixed-use planning are believed to help crime prevention by increased guardianship. However, conditioning on the social features and mobility features, columns 3 and 6 in Table 2 imply that areas with high density of POIs are more likely to be dangerous than they look. In this experiment,the diversity of POIs does not explain the variation of “perception bias” anymore.

4.2.1. Variety and number of amenities

To unpack the type of amenities that could explain the “perception bias,” we include two amenities: retails and education facilities in our models in Table 3. The rational for this choice is that these two types of facilities are found to be spatially correlated with crime events (Wang et al., 2017). Here columns 1, 4 and 7 are our baseline models. All models control the number of visitors at 6 pm and 2 am. In column 2, 5, 8, we include the number of retails and education facilities. Finally, in column 3, 6, 9, we include dummy variables for the retail and education facilities.

The estimates in all models show that the existence of education facilities matters in the discussion of “perception bias.” Columns 2, 3, 5 and 6 show that with the number of education facilities increases, local crime rates are more likely to be higher than their safety scores indicate.

5. Discussion

The results of this paper yield several main takeaways, which we discuss below.

5.1. High safety scores predicted from GSV images are associated with less crime, but there exists a mismatch between the two.

Related to fear of crime, the perception of safety in cities has been studied with rather loose definitions in different literature. This study contributes to the literature by estimating one aspect of the perception of safety in cities - how safe people will rate a street view by its physical appearance. Using a pre-trained computer vision model, we are able to rate perception of the safety of street view images in Houston and derive a safety score at the census block group level. Images (Fig. 2) with high

Table 2
Perception bias: ordinal regression.

	Perception Bias: More Dangerous < Similar < Safer (than it looks)					
	Violent Crimes per Thousand Residents			Other Crimes per Thousand Residents		
	(1)	(2)	(3)	(4)	(5)	(6)
Socioeconomic						
Log (Population)	0.315***	0.340***	0.256***	0.202**	0.260**	0.167
	(0.101)	(0.130)	(0.143)	(0.094)	(0.127)	(0.139)
Log (Population Density)	−0.318***	0.029***	0.143	−0.074	0.169	0.291***
	(0.100)	(0.118)	(0.140)	(0.094)	(0.118)	(0.139)
Ethnic Diversity index	0.002	−0.046	−0.032	−0.088	−0.102	−0.090
	(0.104)	(0.103)	(0.102)	(0.097)	(0.097)	(0.098)
% Unemployment	−0.256***	−0.202***	−0.192***	−0.196***	−0.157*	−0.144
	(0.094)	(0.090)	(0.091)	(0.089)	(0.087)	(0.088)
Urban livelihood						
Log (Visitors @ 2 am)		−0.848***	−0.859***		−0.706***	−0.719***
		(0.183)	(0.190)		(0.180)	(0.182)
Log (Visitors @ 6 pm)		1.140***	1.262***		0.863***	1.029***
		(0.188)	(0.208)		(0.177)	(0.192)
Urban Diversity						
Log (POI Density)			−0.264*			−0.310**
			(0.157)			(0.155)
POI Diversity			0.087			0.031
			(0.139)			(0.137)
Observation	1089	1089	1089	1089	1089	1089

Note: This table reports the ordinal logistic regression coefficients of “Perception Bias”. Standard errors are in parentheses. All parameters are standardized by subtracting their mean and divided by their standard deviation. The dependent variable is the perception bias measured using three ordered categories: *more dangerous than it looks*, *similar*, and *safer than it looks*. * * * denotes a coefficient significant at the 1% level, ** at the 5% level, and * at the 10% level.

Fig. 7. Differences among the coefficients and significance of parameters for two models corresponding to Table 2. Columns 3 and 6.

safety scores usually contain elements such as pruned trees, clean streets, and well-maintained yards, which corresponds to signs of "cues to care" (Nasar et al., 1993; Troy et al., 2016). In contrast, images with low safety scores are found to contain more signs of physical disorder (Doran and Lees, 2005; Wei et al., 2005) such as trash, broken pieces of road, and overgrown vegetation. We found that an increased safety score is associated with fewer crimes controlling for other neighborhood features such as population, ethnic composition, and economic status. This result confirms that the predicted safety score by a computer vision model contains valid information to describe cities. The remaining variance in the model encourages us to unpack further relationships between the perception of safety and crimes in cities.

5.2. *Perception bias and neighborhood socioeconomic features*

In the second part of the paper, we construct a "perception bias" variable that describes the cities with three ordinal categories: "more dangerous than it looks," "similar," "safer than it looks." Using a series of

Table 3
Perception bias and amenities: ordinal regression.

	Perception Bias: More Dangerous < Similar < Safer (than it looks)					
	Violent Crimes per Thousand Residents			Other Crimes per Thousand Residents		
	(1)	(2)	(3)	(4)	(5)	(6)
Log (Population)	0.265**	0.368***	0.333***	0.158	0.277***	0.244**
	(0.143)	(0.133)	(0.131)	(0.134)	(0.128)	(0.129)
Log (Population Density)	0.142	−0.007	0.002	0.283***	0.115	0.130
	(0.141)	(0.119)	(0.119)	(0.133)	(0.117)	(0.116)
Log (Visitors @ 2 am)	−0.905***	−0.883***	−0.827***	−0.741***	−0.717***	−0.670***
	(0.193)	(0.184)	(0.187)	(0.175)	(0.176)	(0.183)
Log (Visitors @ 6 pm)	1.308***	1.249***	1.212***	1.036***	0.948***	0.914***
	(0.213)	(0.195)	(0.193)	(0.183)	(0.179)	(0.180)
Log (POI Density)	−0.282**			−0.325***		
	(0.162)			(0.148)		
POI Diversity Index	0.089			0.037		
	(0.142)			(0.130)		
Retails Dummy		0.018			−0.035	
		(0.087)			(0.083)	
Education Facilities Dummy		−0.260***			−0.268***	
		(0.092)			(0.088)	
Number of Retails			0.076			0.025
			(0.097)			(0.096)
Number of Education Facilities			−0.281***			−0.252***
			(0.101)			(0.098)
Observation	1089	1089	1089	1089	1089	1089

ordinal regression models, we unpack the urban factors contributing to the existing "perception bias." Our results elucidated that unemployment rate is associated with areas that are more dangerous than they look, especially considering violent crimes. This result resonates with the study in social disorganization theories that the neighborhood with economic deprivation (Breetzke, 2010; O'Brien and Sampson, 2015) tends to lead to violent conflicts. Here we emphasize the potential perception bias especially for people who are not familiar with the neighborhood: as these areas are more dangerous than they look, they might deserve more crime prevention interventions as visitors would not be alerted by their physical settings. On the contrary, areas with increased ethnic heterogeneity have more crimes, but do not imply significant "perception bias."

5.3. Perception bias and number of visitors

In addition, our results found that the number of visitors at different times of day has a very different association with the "perception bias". Areas with higher numbers of visitors at 6 pm are more likely to be safer than they look, whereas places with higher numbers of visitors at 2 am are more dangerous than they look. This finding partially supports the "eyes on the street" (Jacobs, 1961) statement that places attracting visitors will provide more guardianship. However, more street activities during the night could have reverse effects. Also, a high volume of visitors at 2 am indicates a higher level of non-routine activities that could be associated with criminal activities themselves. Our study complements to the discussion of ambient population (average population in a given area at different times of day) in criminology (Anderson, 2007). The dynamic number of visitors is an important variable in crime related studies, especially in cities like Houston that exhibit large differences between the census residential population and ambient population.

5.4. Perception bias, density and mixed-use development in cities

Lastly, we show that areas with denser uses are more likely to have higher non-violent crime rates but still look safe. This finding supports the literature that challenges the effects of dense development in crime prevention (Kitchen and Schneider, 2007; Dempsey, 2008). On the contrary, dense uses create "awareness spaces" and could potentially provide increased and more diverse opportunities for crime (Brantingham and Brantingham, 1995). Additionally, the diversity of POIs and the number of retails do not exhibit a significant association with the "perception bias," which indicates that places with diverse uses generally have a good balance between reported crimes and perception of safety. Moreover, our results also indicate school campuses are in general well maintained and might appear peaceful, but they are also areas with high risks of crime. This finding warrants further studies to interpret. It might indicate that students are less cautious to prevent crime or school campuses attract crimes.

5.5. Discussion in the context of other studies

Prior researches in urban planning and environmental criminology share a common agreement that a sustainable community needs to be safe from crime as well as perceived to be safe by its residents. However, without a clarification that perception of safety and safe from crime could have different association with other urban factors, these studies inevitably present conflicting statements with each other when discussing certain features such as high density and mixed-use design in crime control and sustainable urban development (Jacobs, 1993; Bentley, 1985; Dempsey, 2008; Kitchen and Schneider, 2007). Most of these works that connect cities and crimes identify static urban attributes that are systematically associated with the dynamic occurrence of crime and develop urban design strategies in a formulaic fashion for crime prevention. Our study differs from the work mentioned above in two dimensions. First, we use safety scores to show the overall perception of safety induced by scenes taken from the built-environment instead of evaluating individual features such as street permeability, connectivity, and legibility. As such, we circumvent the limitation of applying context-sensitive indicators to measure the influence of the built-environment on criminality. Second, we include dynamic human activity patterns as well as nodes of activity in our study. This approach recognizes the inherent dynamic characteristic of criminality, and it avoids planning conclusions based on static features such as density and mixed-use development promoted by New Urbanism (Ellis, 2002; Cozens, 2008). Instead, our work complements recent literature in environmental criminology that advocates understanding the city's performance at different times and spaces as a totality (Anderson, 2007).

Finally, our approach contributes to the growing literature focused on using crowd-sourced data to improve our understanding of how people behave in cities (Salesses et al., 2013; Zhang et al., 2020). In practice, our work demonstrates how urban planners could adopt recently developed technologies to better manage urban systems. For example, many post-industrial cities in the U.S. such as Philadelphia and Pittsburgh have been developing programs to clean up vacant lots in order to prevent further decay and crimes. Programs as such could use our methods to evaluate the crime-related impact of vacant lots in cities.

5.6. Limitations

While our study has made key contributions, we acknowledge the limitations as following. First, we acknowledge that our measure of perception of safety using predicted value from GSV images only captures one aspect of sense of safety in cities, which might be biased as pointed in existing studies (Huang et al., 2020). Therefore, it does not intend to replace surveys that ask people's perception of safety by their daily experience. Second, using the census block group as a study unit does not fully capture neighborhood characteristics such as income inequality (Wang and Arnold, 2008) and population turnovers that prior studies have indicated strong connection with crimes. Further studies could consider using larger geographical units and expand the studies to more cities. Third, since our hourly visit data provided by SafeGraph was estimated from mobile phone usage, we recognize that the data collected could contain bias towards more active smart-phone users. Finally, as discussed above, the residential population differs from the daytime active population in Houston, thus using the crime rate as a measure in constructing the "perception bias" does not fully represent the real population at risk.

Further study could investigate the urban characteristics and safety perception bias at a finer scale. For example, aggregating the safety perception score at a street level and comparing the local frequency of crime events could give us refined understanding of the above discussed subject. Studies could further estimate the factors that explain perception of bias at individual level. Moreover, including other time sensitive attributes such as degree of street lights (O'Connell, 2017) and opening time of nightlife related amenities such as bars and restaurants could also add explanatory power to describe the time dynamics of crime. Finally, further works could include observed changes in the built environment and trend of crime through years to show how existing perception bias has evolved through time. All these efforts will give further support to create a sustainable urban environment that protects citizens from crime as well as a mentally safer environment that protects the neighborhood from the spread of fear.

6. Conclusion

Despite the existing literature on the intertwined relationships between crime, fear of crimes, and cities, few studies have systematically compared the difference between crime and perception of safety in an urban environment, nor studied the potential factors that contribute to this mismatch. This paper leverages the current development in computer vision techniques, public available street view data and the geography of crimes in the city of Houston to better measure the existing discrepancy between crime and perception of safety: a "perception bias." We explore the association between "perception bias" and three major urban features—socioeconomic features, urban livelihood and urban diversity—that are important to support a sustainable urban environment as well as crime control. We believe this work is of significance both to urban policy makers in designing urban management strategies, and also to those working in urban science, in throwing light on how recently developed techniques can be adopted in understanding cities.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Fan Zhang: Conceptualization, Data curation, Methodology, Software, Writing - review & editing, Project administration, Funding acquisition. **Zhuangyuan Fan:** Conceptualization, Methodology, Data curation, Validation, Writing - original draft, Writing - review & editing, Visualization. **Yuhao Kang:** Data curation, Validation, Writing - review & editing. **Yujie Hu:** Data curation, Validation, Writing - review & editing. **Carlo Ratti:** Funding acquisition, Supervision.

Acknowledgements

The authors would like to thank the anonymous reviewers for their valuable comments and suggestions on earlier versions of the manuscript. This work is supported by the National Natural Science Foundation of China under Grant 41901321 and 41830645. We thank all of the members of the MIT Senseable City Laboratory Consortium for supporting this research.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.landurbplan.2020.104003.

References

Anderson, T. (2007). Comparison of spatial methods for measuring road accident 'hotspots': A case study of london. *Journal of Maps, 3*(1), 55–63.
Bentley, I. (1985). *Responsive environments: A manual for designers*. Routledge.
Brantingham, P., & Brantingham, P. (1995). Criminality of place. *European Journal on Criminal Policy and Research, 3*(3), 5–26.
Breetzke, G. D. (2010). Modeling violent crime rates: A test of social disorganization in the city of tshwane, south africa. *Journal of Criminal Justice, 38*(4), 446–452.
Brown, B. B., & Bentley, D. L. (1993). Residential burglars judge risk: The role of territoriality. *Journal of Environmental Psychology, 13*(1), 51–61.
Bürkner, P. -C. (2017). Advanced bayesian multilevel modeling with the r package brms. arXiv preprint arXiv:1705.11123.
Cahill, M., & Mulligan, G. (2007). Using geographically weighted regression to explore local crime patterns. *Social Science Computer Review, 25*(2), 174–193.
Cordner, G. (2016). Reducing fear of crime.
Cozens, P. M. (2008). New urbanism, crime and the suburbs: A review of the evidence. *Urban Policy and Research, 26*(4), 429–444.
Cozens, P. M. (2011). Urban planning and environmental criminology: Towards a new perspective for safer cities. *Planning Practice and Research, 26*(4), 481–508.
Cozens, P. M. (2011). Urban planning and environmental criminology: Towards a new perspective for safer cities. *Planning Practice and Research, 26*(4), 481–508.
De Nadai, M., Xu, Y., Letouzé, E., González, M. C. & Lepri, B. (2020). Socio-economic, built environment, and mobility conditions associated with crime: A study of multiple cities. arXiv preprint arXiv:2004.05822.
Dempsey, N. (2008). Quality of the built environment in urban neighbourhoods. *Planning, Practice & Research, 23*(2), 249–264.
Ditton, J., & Farrall, S. (2017). *The fear of crime*. Routledge.
Doran, B. J., & Burgess, M. B. (2011). *Putting fear of crime on the map: Investigating perceptions of crime using geographic information systems*. Springer Science & Business Media.
Doran, B. J., & Lees, B. G. (2005). Investigating the spatiotemporal links between disorder, crime, and the fear of crime. *The Professional Geographer, 57*(1), 1–12.
Dubey, A., Naik, N., Parikh, D., Raskar, R. & Hidalgo, C. A. (2016). Deep learning the city: Quantifying urban perception at a global scale. In European conference on computer vision (pp. 196–212). Springer.
Eck, J. E., Clarke, R. V., Guerette, R. T., et al. (2007). Risky facilities: Crime concentration in homogeneous sets of establishments and facilities. *Crime Prevention Studies, 21*, 225.
Ellis, C. (2002). The new urbanism: Critiques and rebuttals. *Journal of Urban Design, 7*(3), 261–291.
Fuhrmann, S., Huynh, N. T., & Scholz, R. (2013). Comparing fear of crime and crime statistics on a university campus. In *Crime modeling and mapping using geospatial technologies* (pp. 319–337). Springer.
Furstenberg, F. F. (1971). Public reaction to crime in the streets. *The American Scholar*, 601–610.
Glaeser, E. L., & Sacerdote, B. (1999). Why is there more crime in cities? *Journal of Political Economy, 107*(S6), S225–S258.
Goodchild, M. F., & Haining, R. P. (2004). Gis and spatial data analysis: Converging perspectives. *Papers in Regional Science, 83*(1), 363–385.
Grant, J. (2002). Mixed use in theory and practice: Canadian experience with implementing a planning principle. *Journal of the American Planning Association, 68*(1), 71–84.
Harries, K. D. (1995). Mapping crime: Principle and practice. US Department of Justice, Office of Justice Programs, National Institute of....
Henson, B., & Reyns, B. W. (2015). The only thing we have to fear is fear itself...and crime: The current state of the fear of crime literature and where it should go next: The only thing we have to fear. *Sociology Compass, 9*(2), 91–103.
Huang, Y., Li, J., Wu, G., & Fei, T. (2020). Quantifying the bias in place emotion extracted from photos on social networking sites: A case study on a university campus. *Cities, 102*, 102719.
Jacobs, A. B. (1993). Great streets. *ACCESS Magazine, 1*(3).
Jacobs, J. (1961). *The death and life of great American cities*. Vintage.
Jeffery, C. R. (1971). *Crime prevention through environmental design* (Vol. 91). CA: Sage Publications Beverly Hills.
Kinney, J. B., Brantingham, P. L., Wuschke, K., Kirk, M. G., & Brantingham, P. J. (2008). Crime attractors, generators and detractors: Land use and urban crime opportunities. *Built Environment, 34*(1), 62–74.
Kitchen, T., & Schneider, R. H. (2007). *Crime prevention and the built environment*. Routledge.
Kohm, S. A. (2009). Spatial dimensions of fear in a high-crime community: Fear of crime or fear of disorder? *Canadian Journal of Criminology and Criminal Justice, 51*(1), 1–30.
Liu, L., & Eck, J. (2008). *Artificial crime analysis systems: Using computer simulations and geographic information systems*. IGI Global.
McIntyre, J. (1967). Public attitudes toward crime and law enforcement. *The Annals of the American Academy of Political and Social Science, 374*(1), 34–46.
Moore, M. H. & Trojanowicz, R. C. (1988). Policing and the fear of crime. Number 3. US Department of Justice, National Institute of Justice.
Naik, N., Philipoom, J., Raskar, R., & Hidalgo, C. (2014). Streetscore-predicting the perceived safety of one million streetscapes. In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops* (pp. 779–785).
Nasar, J. L., Fisher, B., & Grannis, M. (1993). Proximate physical cues to fear of crime. *Landscape and Urban Planning, 26*(1–4), 161–178.
Newman, O. (1972). *Defensible space*. Macmillan New York.
O'Connell, H. (2017). What happens in the shadows: Streetlights and how they relate to crime.
O'Brien, D. T., & Sampson, R. J. (2015). Public and private spheres of neighborhood disorder: Assessing pathways to violence using large-scale digital records. *Journal of Research in Crime and Delinquency, 52*(4), 486–510.
Pánek, J., Ivan, I., & Macková, L. (2019). Comparing residents' fear of crime with recorded crime data—-case study of ostrava, czech republic. *ISPRS International Journal of Geo-Information, 8*(9), 401.
Rantala, R. R. (2000). Effects of NIBRS on crime statistics. US Department of Justice, Office of Justice Programs, Bureau of Justice....
Ratcliffe, J. H. (2004). Geocoding crime and a first estimate of a minimum acceptable hit rate. *International Journal of Geographical Information Science, 18*(1), 61–72.
Salesses, P., Schechtner, K., & Hidalgo, C. A. (2013). The collaborative image of the city: Mapping the inequality of urban perception. *PLoS One, 8*(7). e68400.
Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science, 277*(5328), 918–924.
Schweitzer, J. H., Kim, J. W., & Mackin, J. R. (1999). The impact of the built environment on crime and fear of crime in urban neighborhoods. *Journal of Urban Technology, 6*(3), 59–73.
Shaw, C. R. (1929). Delinquency areas.
Skogan, W. (1986). Fear of crime and neighborhood change. *Crime and Justice, 8*, 203–229.
Snyders, E., & Landman, K. (2018). Perceptions of crime hot-spots and real locations of crime incidents in two south african neighbourhoods. *Security Journal, 31*(1), 265–284.
Solymosi, R., Bowers, K., & Fujiyama, T. (2015). Mapping fear of crime as a context-dependent everyday experience that varies in space and time. *Legal and Criminological Psychology, 20*(2), 193–211.
Song, G., Liu, L., He, S., Cai, L., & Xu, C. (2020). Safety perceptions among african migrants in Guangzhou and Foshan, China. *Cities, 99*, 102624.
Toet, A., & van Schaik, M. G. (2012). Effects of signals of disorder on fear of crime in real and virtual environments. *Journal of Environmental Psychology, 32*(3), 260–276.

Troy, A., Nunery, A., & Grove, J. M. (2016). The relationship between residential yard management and neighborhood crime: An analysis from baltimore city and county. *Landscape and Urban Planning, 147*, 78–87.

Tuan, Y.-F. (1977). *Space and place: The perspective of experience*. University of Minnesota Press.

Vrij, A., & Winkel, F. W. (1991). Characteristics of the built environment and fear of crime: A research note on interventions in unsafe locations. *Deviant Behavior, 12*(2), 203–215.

Wang, F., & Arnold, M. T. (2008). Localized income inequality, concentrated disadvantage and homicide. *Applied Geography, 28*(4), 259–270.

Wang, F., Hu, Y., Wang, S., & Li, X. (2017). Local indicator of colocation quotient with a statistical significance test: Examining spatial association of crime and facilities. *The Professional Geographer, 69*(1), 22–31.

Warr, M. (1990). Dangerous situations: Social context and fear of victimization. *Social Forces, 68*(3), 891–907.

Warr, M. (2000). Fear of crime in the united states: Avenues for research and policy. *Criminal Justice, 4*(4), 451–489.

Wei, E., Hipwell, A., Pardini, D., Beyers, J. M., & Loeber, R. (2005). Block observations of neighbourhood physical disorder are associated with neighbourhood crime, firearm injuries and deaths, and teen births. *Journal of Epidemiology & Community Health, 59*(10), 904–908.

Wilson, J. Q., & Kelling, G. L. (1982). Broken windows. *Atlantic Monthly, 249*(3), 29–38.

Zhang, F., Zhou, B., Liu, L., Liu, Y., Fung, H. H., Lin, H., & Ratti, C. (2018). Measuring human perceptions of a large-scale urban region using machine learning. *Landscape and Urban Planning, 180*, 148–160.

Zhang, F., Zu, J., Hu, M., Zhu, D., Kang, Y., Gao, S., Zhang, Y., & Huang, Z. (2020). Uncovering inconspicuous places using social media check-ins and street view images. *Computers, Environment and Urban Systems, 81*, 101478.