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Investigating the effect of people on the street and streetscape physical environment on the location choice of street theft crime offenders using street view images and a discrete spatial choice model

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ABSTRACT

As street crime occurs in the street, it is reasonable to assume that the location choice of street crime offenders is affected by streetscape conditions and people on street. However, this issue has not been investigated by previous research, possibly because fine-grained streetscape data are hard to obtain. Traditional data-gathering methods like questionnaires, field surveys, and manual audits are inefficient and only applied to small areas. Social media and mobile phone data have recently been used to measure the ambient population. However, they are unable to distinguish between indoor and on-street people. To overcome these limitations, the present research applied an integrative deep learning algorithm combining an object detection network and a semantic segmentation network to extract on-street people and physical environment elements from fine-grained street view images (SVIs) in a large Chinese city. The extracted elements include fences, walls, windows, grass, sidewalk, and plants. Controlling the influence of residence-crime proximity, crime attractors, generators, detractors, and socioeconomic features, we constructed a discrete spatial choice model to investigate the influence of people on the street and the streetscape's physical environments on the location choice of street theft crime offenders. Results reveal an improvement in model performance after the streetscape variables are considered. Therefore, the streetscape context is essential for understanding offenders' preferences for crime locations. Specifically, the number of people on the street presents a significantly positive relationship with the offenders' preferences. Fences and plants have significant and positive effects on attracting criminals. Grasses and sidewalks negatively affect offenders' location choices. Walls and windows do not significantly affect criminals' crime location choices. Additionally, the associations between most control variables and offenders' preferences for crime locations conform to previous research findings. As the first attempt in combining SVIs, deep learning algorithms, and discrete spatial choice model, this study makes a contribution to the extant crime location choice literature.

1. Introduction

Street crime is not only a threat to human life and property safety, but it may also undermine the willingness of people to visit the places where such crimes frequently occur. In order to make suggestions for crime prevention and control tasks, many researchers have studied the occurrence regularity of crime from different angles. Among these, crime location choice has gained influence in the past two decades. Crime location choice focuses on where offenders implement offenses and why they choose these places instead of elsewhere (Bernasco & Nieuwbeerta, 2005).

Previous studies have demonstrated that crime location choice is a complex process and that various factors affect offenders' final decisions. For example, offenders typically select the neighborhoods they live in or have lived in as their primary crime targets (Bernasco, 2010). Individual characteristics like age (Andresen, Frank, & Felson, 2013; Levine & Lee, 2013; Xiao, Liu, Song, Ruiter, & Zhou, 2018), gender (Levine & Lee, 2013), ethnicity (Bernasco & Block, 2009; Levine & Lee, 2013), and characteristics of target areas such as the presence of crime generators and crime attractors (Bernasco & Block, 2009; Kuralarasan & Bernasco, 2021), the guardianship of ambient population and surveillance cameras (Long et al., 2021), the collective efficacy (Bernasco & Block, 2009), and the land use patterns (Stucky & Ottensmann, 2009) have also been shown to influence offenders' location choice behavior.

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Intuitively, the opportunities for street theft crime should be affected by the on-street population and the streetscape physical environment, which in turn influences offenders' location choice strategies. However, the literature has not examined the association between visual streetscape context and offenders' preferences of crime location, possibly due to the lack of detailed data sources.

As an increasingly popular data source in urban research, the emerging street view images (SVIs) have a significant advantage in capturing the urban streetscape environment from pedestrians' points of view (Biljecki & Ito, 2021; Kang, Zhang, Gao, Lin, & Liu, 2020). Additionally, SVIs are fine-grained, and have broad coverage. Thanks to modern image processing techniques, such as deep learning networks, it is convenient and cost-effective to extract large-scale streetscape environmental features from SVIs (Biljecki & Ito, 2021), including artificial elements, natural elements, and pedestrian volumes. Therefore, the integration of SVIs and deep learning allows us to examine the effect of streetscape physical environment and on-street population on offenders' crime location choices.

The main aim of this study is to investigate how the presence of people on the street and the streetscape's physical environment affect criminals' crime location choices. First, this study collected a set of fine-grained SVIs in a megacity in China. Then, using integrated deep learning networks, we detected on-street population and streetscape physical environment features from these images. A discrete spatial choice model is finally constructed to investigate the effect of streetscape features on offenders' crime location choices. Residence-crime proximity, crime attractors, generators, detractors, and socioeconomic attributes of communities are accounted for, as these factors also influence crime location choice.

The remainder of this article is organized as follows. Section 2 systematically reviews related works. Section 3 introduces the study area and the utilized datasets and methodology. Sections 4 and 5 elaborate on the experimental results and our explanations. Finally, we summarize the conclusions in Section 6.

2. Literature review

2.1. Effect of the presence of people on street crime

The crime location choice studies are typically built on the rational choice theory, first proposed by Cornish and Clarke to help explain crime target selection (Cornish & Clarke, 1987). The theory regards criminals as 'rational persons'. It suggests that potential benefits, risks, and costs are three factors to balance when they choose targets. Extant theoretical literature has different views on the effect of the presence of people on street crime. On the one hand, the presence of people can provide targets for criminals. Therefore, locations with more people are more attractive to offenders because more targets may lead to higher potential benefits (Browning & Jackson, 2013). Therefore, areas with dense populations on street are more likely to suffer from street theft crimes. On the other hand, people's presence can act as natural guardians. Jacobs believes that business owners are "eyes on the street" and can act as informal surveillance to deter crime (Jacobs, 1961). Specifically, Jacobs advocates facilitating the continuous use of public spaces to ensure enough informal surveillance. The natural guardianship or informal surveillance effect of people can raise the risk of committing crimes and finally restrain the occurrence of crimes.

Apart from the above theoretical literature, a series of empirical research has examined the impact of the presence of people on the occurrence of street crime at the street segment level. Yue et al. combined SVIs and deep learning approaches to quantify the on-street population and streetscape-built conditions, based on which they examined their effects on street property and violent crime (Yue, Xie, Liu, & Chen, 2022). Results shown a significantly positive impact of the on-street population on street property crime but a non-significant impact on street violent crime. Hipp et al. adopted social media data to measure the population sizes at different locations and times of day and determine whether these measurements help predict the amount of crime over the day (Hipp, Bates, Lichman, & Smyth, 2018). Their study demonstrated that the association between tweets (a proxy of ambient population) and motor vehicle theft was strongest in the middle of the day. As they explained, the presence of more ambient population in this time period increased the number of targets. He et al. used mobile phone data to capture the sizes and activity patterns of different types of ambient population, and examined their effectiveness in understanding larceny theft (including pocket-picking, the theft of electric bicycles, bicycle thefts, etc.) rates (He et al., 2020). They found that the size of the non-local population significantly correlated with the spatial variation of larceny theft.

2.2. Effect of the physical environment on street crime

The physical environment is an essential constituent element of a city and directly affects human activity. Environmental criminology holds that the built environment plays a critical role in the occurrence of crime (a type of human activity in nature) (Brantingham & Brantingham, 1999). Physical environment features are supposed to affect the confluence of motivated offenders, suitable targets, and the absence of qualified guardians, which are three essential elements of the 'crime triangle' (Brantingham & Brantingham, 1999; Cohen & Felson, 1979).

The association between the physical built environment and street crime has been studied majorly from two perspectives. The first type of study is concerned primarily with the macro layout of the city, such as the land use patterns (Sadeek, Minhuz Uddin Ahmed, Hossain, & Hanaoka, 2019; Wo, 2019), the density and morphology of buildings (Fallon & Price, 2020; Yue, Hu, & Lian, 2022), the road network structure (Kim & Hipp, 2019; Summers & Johnson, 2017; Yue, Zhu, Ye, Hu, & Kudva, 2018), etc. These studies are usually conducted to analyze how the macro urban environment shapes the opportunity for street crime and thereby further affects the spatial distribution patterns of crime. Land use pattern has been demonstrated to be related to crime rates. For example, Wo examined how mixed land use affects crime (Wo, 2019). Results shown that vacant and school land uses were negatively associated with motor vehicle theft. They explained that these land uses were crime-reducing because they minimized the probability that offenders and targets will converge in space. A set of studies have also revealed the association between street configuration and crime. For example, Kim and Hipp applied the betweenness centrality to measure potential foot traffic passing through a given street segment (Kim & Hipp, 2019). Using the betweenness centrality measurement, they examined the association between the physical configuration of the street network and the level of crime in place. Their results revealed that street segments with more potential travelers have higher crime risks because of the convergence of more potential criminals and targets. However, when the number of potential travelers on a street segment reaches a certain amount, the number of crimes reduces because of the higher level of natural surveillance from eyes on the street.

Another series of studies emphasize the association between the microscopic physical environment and street crime. Frequently concerned micro-built environment features are the structures or appendants of buildings or streets and the signs of physical disorder. For example, Zeng et al. investigated the association between street environment and street crime (Zeng, Mao, & Wang, 2021, p. 112). They collected detailed street environmental factors like shop length ratio, types of walls, and the presence of street green field through field surveys. Results suggested that the increase of shop length ratio would lead to a significant increase of street theft risk. The probability of theft occurrence would reduce by forty percent on streets with walls compared with streets without walls or fences and usually with shops only. The broken windows theory literature suggests the existence of signs of physical disorder, such as broken windows, abandoned buildings (Spelman, 1993), damaged facilities, litter on the street, untidy vacant lots (O'Brien, Sampson, & Winship, 2015), and illegal graffiti (Loukaitou-Sideris, Liggett, Iseki, & Thurlow, 2016), could induce deviant and criminal behavior (Wilson & Kelling, 1982). Removing or improving the physical disorder conditions is beneficial for constructing defensible spaces and curbing crimes to increase (Paul Cozens & Love, 2015). The Crime Prevention through Environmental Design (CPTED) literature also stresses the critical role the micro-built environment plays in influencing the occurrence of crimes. The CPTED theory suggests that crime reduction could be achieved through proper design and effective usage of the built environment (Crowe, 2000). Specifically, the CPTED strategies contain six components: territoriality (symbolic and real barriers like signs and fences), surveillance (informal, formal, and mechanical surveillance), access control (physical and psychological barriers), image/maintenance (maintain a positive image), activity support (attract safe activities), target hardening (locks and security at points of access).

The existence of crime attractors and crime generators in a given location heightens their appeal to offenders, but the means by which each operates differs. Crime generators generally refer to places where dense crowds congregate, such as transport hubs and shopping malls. While the motivation for people to gather at these locations may not be related to criminal activity, the dense crowds provide potential targets for would-be offenders, with an increased number of opportunities for illicit behavior as crowd density rises. On the other hand, crime attractors denote specific locations that allure offenders with criminal intent, such as drug markets and prostitution sites. These locations frequently showcase opportunities for particular types of crimes. In Chennai, India, Kuralarasan and Bernasco (2021) conducted an analysis of the influence of crime attractors and crime generators on the site selection patterns of snatchers. Their findings revealed that the greater the prevalence of schools, parks, and restaurants in a given area, the more likely it was to be chosen as a site for criminal activity. Johnson and Summers (2015) conducted an analysis of the location selection strategy employed by vehicle theft offenders in Dorset County, UK. The results revealed that schools played a significant role in shaping the awareness spaces of juvenile offenders, which consequently impacted their location choices. However, this type of facility had negligible influence on the spatial decision-making process of adult offenders. Additional facilities, including banks (Kubrin & Hipp, 2014), retail establishments (Bernasco & Block, 2009), and subway stations (Herrmann, Maroko, & Taniguchi, 2021) have also been shown to influence the location selection of theft offenders.

For street crime, streetscape conditions also influence offenders' location choices. Sidewalks are slow-moving paths intended for pedestrians and represent to some degree the existence of potential crime targets. Such areas are high-risk zones for thefts and robberies, with most offenders committing crimes while walking (Xie, Liu, & Yue, 2022). The presence of factors like the proportion of commercial interfaces along both sides of the street, shops facing the street (Zeng et al., 2021, p. 112), and buildings along the street (Hipp, Lee, Ki, & Kim, 2021) indicates the availability of opportunities for crime. This is because crowds inside and around the building provide potential crime targets for offenders. The presence of walls (Hipp et al., 2021), fences (Xie et al., 2022), and other physical elements indicates the level of passage control in an area. These factors restrict the accessibility of the area and increase the difficulty for offenders to escape after committing a crime, thus having a certain degree of inhibitory effect on street crime. The presence of elements such as streetlights (Xu, Fu, Kennedy, Jiang, & Owusu-Agyemang, 2018) and surveillance cameras (Reid & Andresen, 2012) reflects the level of territorial surveillance in an area. Installing street lights or surveillance cameras can increase the probability of offenders being caught or discovered, deter rational potential offenders, and thus reduce crime. Elements such as trees (Ye, Chen, & Li, 2018) and lawns (Troy, Nunery, & Grove, 2016) can provide a pleasing walking environment, thereby elevating the activity support level of an area. Furthermore, open lawns have strong visual permeability, which enables more natural supervision and may decrease the likelihood of crime occurrence (Troy et al., 2016).

2.3. Measurement of streetscape environment

It is relatively easy for researchers to incorporate the social and demographical dimensions of the environment into their studies because the census data released by the government is pervasive and is usually readily accessible. However, it is almost always more challenging to measure the streetscape environment than to measure the social and demographical features of residents living in an area (Hipp, Lee, Ki, & Kim, 2022). Much of the extant research used demographic census data to evaluate the population's exposure to crime (Andresen, 2006; Chamlin & Cochran, 2004). Although the residential population is an accessible and convenient way to estimate population size, it is the total ambient population present in a location rather than the residence that we should consider. Realizing the deficiency of the official census data, researchers have also collected population data through trip surveys. For example, Boivin adopted a telephone transportation survey to collect the visitor inflows with different trip purposes to each area (Boivin, 2018). Based on this data, the study investigated the relationship between human presence and criminal activity.

Data gathering by the survey is time-consuming and labor-intensive, which limits its use in measuring the ambient population. Emerging big data like mobile phone data, geotagged social media, and transport trajectory data are suitable substitutes for census and survey data. Many researchers utilized these data to examine the relationship between human presence and crime. For example, Tucker et al. adopted geotagged Twitter to measure the block-level population sizes of local residents, inter-metro commuters, and tourists. They examined their associations with public violence and private conflict (Tucker et al., 2021). Hanaoka applied mobile phone location data to measure the hourly population and examine its relationship with snatch-and-run offenses and the difference between daytime and nighttime (Hanaoka, 2016). Although these data sources cover a large area and have a high time resolution, their spatial resolutions are usually low. Moreover, they cannot capture the movement of pedestrians, so they cannot distinguish between the street and indoor populations.

Additionally, the micro-scale built environment features of the urban street are particularly difficult to assess because these data are often difficult to obtain. Traditional approaches like questionnaire surveys (Cozens & Davies, 2013), field surveys, and human auditing (He, Páez, & Liu, 2017; Rundle, Bader, Richards, Neckerman, & Teitler, 2011) can collect data about the streetscape environment in as much detail as possible. However, these methods need to consume a colossal workforce and time, which makes them apply only to research in small regions. Remote sensing images supply continuous data resources to environment surveying in a large region (Patino, Duque, Pardo-Pascual, & Ruiz, 2014; Wolfe & Mennis, 2012; Zhou, Liu, Lan, Yang, & Wang, 2019). Nevertheless, remote sensing images are taken from an aerial perspective. They cannot gather information about the streetscape environment from a human's eye view. The lack of large-scale detailed data makes it difficult to quantify the streetscape physical environment systematically, eventually leaving the study of the visual streetscape environment's influence on crime location choice insufficient.

In recent years, computer technology has provided a new data source for measuring the urban street microenvironment. Map service providers such as Google, Baidu, and Tencent have collected street-level images. These street view images are usually freely available. Because street view images are commonly taken by cameras placed on top of street-view cars driving along streets, they capture streetscape conditions approximately from pedestrians' lines of sight. Therefore, street view images have the potential to reveal the most immediate association between the streetscape environment and offenders' crime location choice. Using the emerging deep learning technique, researchers can extract streetscape environment features from street view images in large areas at a low cost.

Several studies have examined the association between street-built environments and crime for the last two years using SVIs. Hipp et al. (2021) utilized a semantic segmentation technique to extract the average pixel proportions of environmental features such as pedestrians, sidewalks, vehicles, fences, and walls from Google Street View images. These measurements were used to evaluate street vitality, motorization levels, defense space, and green space, and to explore the relationship between these micro-environmental features and various types of crime, including burglary, robbery, and motor vehicle theft. The results revealed that pedestrian activity and crime rate were not significantly correlated, but there was a positive correlation between motorization level and crime. Walls were correlated with low-crime risk, while fences were related to motor-vehicle theft. Additionally, the presence of green spaces influenced the occurrence of crime. Similarly, He, Wang, Xie, Wu, and Chen (2022) applied the same method to extract the average pixel proportions of environmental features like walls, windows, and buildings in street view images. They developed scene perception indices, like street enclosure and openness, to reflect the characteristics of streetscape micro-environments, such as territoriality, surveillance, activity support, and image maintenance. Subsequently, they investigated the association between streetscape environments and crime. Moreover, Khorshidi, Carter, Mohler, and Tita (2021) identified objects from Google Street View images to develop an object diversity index and investigated the relationship between streetscape environmental diversity and crime diversity. The findings indicated that streetscape environmental diversity could better explain crime diversity than most traditional socio-economic variables. Other studies combining street view images and deep learning to examine the occurrence of crime include Luo, Deng, Shi, Gao, and Liu (2022), Xie et al. (2022), Yue, Hu, and Lian (2022), and Zhou et al. (2021).

Although street view images are used by an increasing number of studies to measure streetscape environment features, most extant literature uses a semantic segmentation approach to extract physical elements such as buildings, roads, and vegetation. Detecting elements without fixed shapes and distinct outlines using pixel-wise semantic segmentation is reasonable. Nevertheless, it is more suitable to use object detection methods to determine their numbers for detecting discrete elements with distinct outlines, like persons. The on-street population, an essential variable affecting street crime, has not been considered by previous research.

3. Research design

3.1. Study area

This study is conducted in ZG city, a megacity in southeast China. With an urbanization rate of 86.46%, the population of permanent residents in the city amounted to 15.30 million in 2019. There are 2643 communities in the ZG city, and this study takes the community as the spatial unit of analysis.

Because of the high urbanization rate, buildings and roads do generally not change significantly from one year to another. Being situated in a sub-tropical region, trees and bushes remain green throughout the year. Therefore, street view images in ZG, unlike those in high latitude cities, do not have much seasonal variations.

3.2. Data

3.2.1. Streetscape features

- *Baidu Street View images*

This study adopted Baidu Street View (BSV) images as the data source to detect people on the street and other streetscape physical environment features. To download BSV images, we first generated a sampling point every 20m along the street segment, as presented in Fig. 1. SVIs are captured by cameras set on top of cars driving along streets. There may be no SVIs on some streets as the street view cars may not drive through these streets. Therefore, no SVIs can be downloaded on some sampling points. To ensure that the street networks in each community have adequate SVIs, we calculated the coverage rate of SVIs in each community as the percentage of the number of SVI points versus the number of all sampling points. Then, communities with coverage rates of SVIs less than 50% were dropped. Finally, 1636 communities remain in this study. Fig. 2 illustrates the study area, communities, and sampling points. Only 5% of the sampling points are displayed in the figure for enhanced visual clarity.

For each sampling point, we calculated four azimuth angles; two are parallel to the street, while the other two are vertical to the street. The pitch angles are 0°. These parameters are set to be consistent with pedestrians' experience when walking along the street. Passing the coordinate (latitude and longitude), the azimuth angle, and the pitch angle of a sampling point into the BSV API, we can download four BSV images at each sampling point.

Baidu Street View Map does not provide images for the entire year of 2018. We selected street view images captured in 2016, 2017, and 2019, to align with the time period of the crime data (2017–2018) and to ensure that the spatial coverage is sufficient for the study. When downloading BSV images for a specific sampling point, we selected images from 2017 if available at that location, and if not, we selected images from either 2016 or 2019. In total, we obtained 3,871,916 BSV images. Since our study area is located in the inner city of ZG, the built environment is not expected to change significantly. Therefore, we believe that the crime data and SVIs are reasonably matched in time.

- *Detect people on the street using an object detection network*

Persons are discrete and countable elements with distinct outlines in

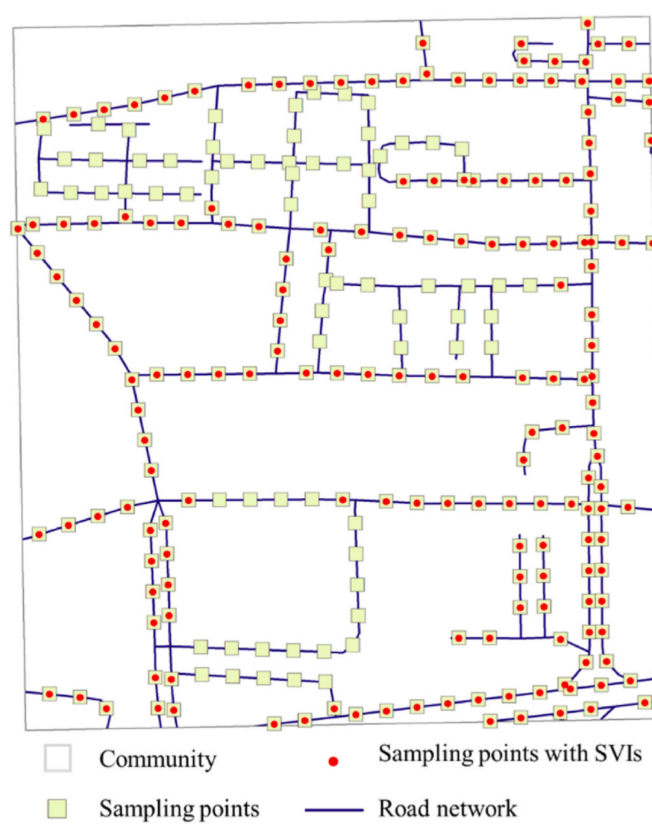

Fig. 1. Sampling points with and without SVIs along the street.

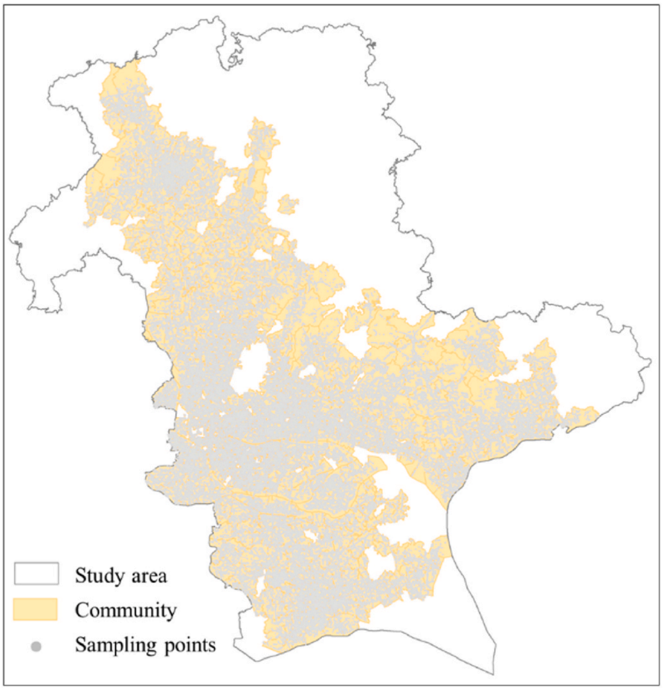

Fig. 2. Study area, communities, and sampling points.

an image. This study adopted a pretrained Faster R-CNN (Region-based Convolutional Neural Network) object detection network (Ren, He, Girshick, & Sun, 2015) to detect people on the street based on the BSV images. The network is trained on the MS COCO dataset with ResNeSt-269 backbone (Zhang et al., 2022). Average precisions (AP) at various IoU (intersection over union) thresholds are commonly used to evaluate model performance. IoU quantifies the overlap between the predicted bounding boxes and the ground truth bounding boxes. The network we used in this study has good performance: the average AP for IoU from 0.5 to 0.95 with a step size of 0.05 is 46.5%, the average AP at IoU = 0.5 is 67.5%, and the average AP at IoU = 0.75 is 50.7%, which is considered very good for object detection. In brief, the Faster R-CNN object detection network used in this study achieves top-tier performance.

The outputs of the Faster R-CNN network are a group of boxes marking the bounding rectangles of detected objects in an image. Each box is accompanied by a label denoting the type of the object inside and a value representing the probability that the box contains the object. We counted the number of people on the street in a community using the following formula:

$$Number\ of\ people\ on\ the\ street = \sum_{i=1}^{n} \sum_{j=1}^{4} Person_{Image\_ij} \quad (1)$$

where *Image_ij* represents the BSV image taken in the *j*th direction at *i*th sampling point, *n* means the total number of sampling points within a community.

To validate the accuracy of the Faster R-CNN object detection network used in this study, 50 images were randomly selected from the collected street view images. The number of on-street population in each image was observed and recorded through visual inspection, serving as the ground truth, while the results detected by the Faster R-CNN network were used as the predicted results. Frequency distribution of the differences between the predicted and ground truth results are shown in Fig. 3. The results indicate minimal discrepancies, with differences concentrated around 0, suggesting high accuracy of the Faster R-CNN network. Furthermore, a strong correlation was calculated between the predicted and ground truth results (correlation coefficient r = 0.840, p-value < 0.01).

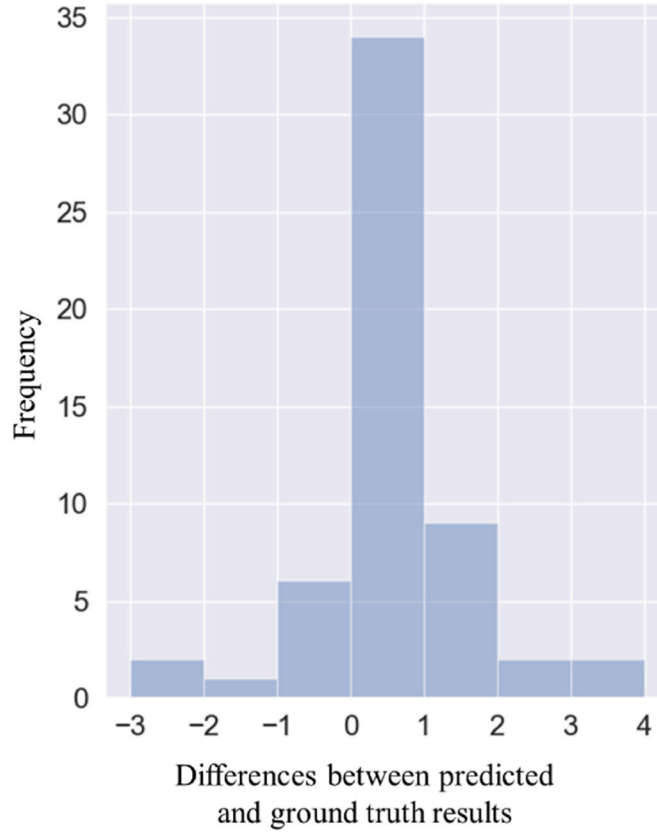

Fig. 3. Frequency distribution of on-street population detection differences.

- *Extract physical environment features using a semantic segmentation network*

Physical environment elements like buildings, roads, and trees do not have definitive shapes, so the object detection network does not apply to them. Instead, this study extracted a set of streetscape physical environment features related to street crime using a semantic segmentation technique. Semantic segmentation is a classification task at the pixel level; pixels belonging to the same category are classified into one class.

This study applied the widely used Pyramid Scene Parsing Network (PSPNet) (Zhao, Shi, Qi, Wang, & Jia, 2017) to generate pixel-wise predictions and assign each pixel a category label for each BSV image. The network is trained on the ADE20K dataset with ResNet-101 backbone (Zhao et al., 2017). PSPNet has achieved top performance on various semantic segmentation benchmark datasets like ADE20K. It often achieves mean intersection over union (mIoU) scores above 0.8, indicating high accuracy in capturing object boundaries and generating accurate segmentations.

Using the PSPNet semantic segmentation network, we can obtain the percentages of different elements in each image. Then, we measured the overall ratio of each type of element in a community as follows:

$$Percent\ of\ element = \frac{\sum_{i=1}^{n} \sum_{j=1}^{4} PixelE_{Image\_ij}}{\sum_{i=1}^{n} \sum_{j=1}^{4} PixelT_{Image\_ij}} \times 100\% \quad (2)$$

where *Image_ij* is the BSV image taken in the *j*th direction at the *i*th sampling point. *PixelE* is the number of pixels belonging to type *E* in an image, and *PixelT* represents the total number of pixels in that image.

Additionally, the accuracy of the PSPNet semantic segmentation network used in this study was validated. Each pixel of the 50 selected street view images was manually annotated to serve as the ground truth. The predicted results were obtained from the PSPNet network. Pixel-level accuracy, a commonly used metric, was employed to evaluate the accuracy of the PSPNet network. Specifically, the pixel-level accuracy was calculated for each image by comparing the predicted results with the manually annotated ground truth and computing the proportion of correctly predicted pixels. The average accuracy of the 50 images was then calculated to evaluate the overall accuracy of the PSPNet network. Higher pixel-level accuracy values indicate greater consistency between the network's predicted results and the ground truth. As depicted in Fig. 4, the results demonstrate that the pixel-level accuracy of most images is above 0.8, with an average pixel-level accuracy of 0.849 for the 50 images. This finding suggests that the PSPNet network used in this study produces highly consistent semantic segmentation results with the ground truth, indicating a high level of accuracy.

As summarized in Fig. 5, this study extracted seven street view variables from BSV images using an object detection network and a semantic segmentation network. They are the number of people on the street (per 1000), the mean percentage of fences (percent fence, %), the mean percentage of walls (percent wall, %), the mean percentage of windows (percent window, %), the mean percentage of grasses (percent grass, %), the mean percentage of sidewalks (percent sidewalk, %), and the mean percentage of plants (percent plant, %).

3.2.2. Crime data

The type of crime studied in this paper is street theft crime, which includes snatching, pickpocketing, and theft from the person that happened in the public open space. We obtained a set of detected street theft crimes committed during 2017 and 2018 from the police department of ZG city. It contains the location, date, and time of the crime, as well as the address, age, and gender of the offender who committed the crime. Crimes committed jointly by multiple offenders (co-offending) and committed by offenders whose residential addresses were not in ZG city were excluded from this study. It is reasonable to assume that the streetscape environment has a limited influence on crime in buses and subways, so we did not include crimes in these locations. Finally, there were 1540 street theft crimes in the selected communities of the study area.

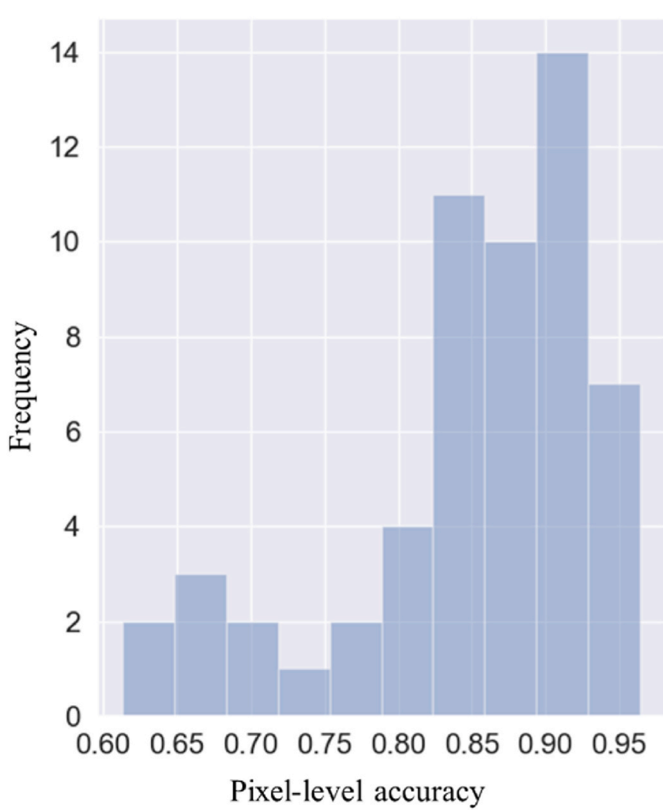

Fig. 4. Frequency distribution of pixel-level accuracy.

3.2.3. Distance of journey to crime

As extant literature has proved that the distance from an offender's residence plays a prominent role in the offender's crime location choice, this study also accounts for this effect. For each detected street theft crime, we calculated the distance between the offender's residence and the centroids of each of the 1636 communities. To make the hypothesized effect positive, we constructed an offender residence-crime proximity variable by reversing the residence-crime distance.

3.2.4. Crime attractors, generators, and detractors

Crime is usually clustered in space, Brantingham and Brantingham (Brantingham & Brantingham, 1995) classified places where crime frequently happens as crime attractors and crime generators. Crime generators like subway stations and bus stops usually gather a large number of people. Although people may not come to these places with explicit criminal intent, they may be motivated by the crime opportunities provided by the large crowds here. Crime attractors are susceptible to crimes because of the specific crime opportunities in these places. Such places include drug markets and prostitution sites. These places do not necessarily draw a large crowd; however, their functions make them suitable places for potential offenders to find attractive targets (Bernasco & Block, 2011). Although the classification of crime generators and attractors, a particular place is unlikely to be a pure crime attractor or generator. Due to the similar characteristics of crime attractors and generators, we did not distinguish between them and combined them into one variable. Specifically, we included the number of ATMs and banks, subway stations, bus stops, schools, and hospitals. Additionally, crime detractors like security guards and CCTV may deter potential offenders and criminal behaviors (Kinney, Brantingham, Wuschke, Kirk, & Brantingham, 2008). Therefore, this study used the number of police stations and security guard stations to represent crime detractors.

3.2.5. Socioeconomic features

Based on the social disorganization theory, neighborhoods with greater residential stability, racial homogeneity, and higher socioeconomic status are more cohesive. Residents in cohesive communities can comprehend their common interests and preserve effective social control (Steenbeek & Hipp, 2011). This study considered two socioeconomic features in the context of social disorganization: percent migrants and percent lowly-rent houses. Percent migrants refers to the proportion of people who do not have a Hukou in ZG City. Hukou is a local residence permit that entitles a person to essential social services. People who do not have a Hukou in a city are usually migrants (usually for work or study) from other cities. These migrants may dilute local residents' social connection and impair their ability to achieve consensus, which is unfavorable for forming informal control (Sampson & Groves, 1989). Percent lowly-rent houses is a proxy of income level. It represents the proportion of rental houses with rent fees lower than 1000 RMB per month. The higher the income level, the higher people's socioeconomic status may be. Wealthy neighborhoods usually have strong formal controls. Additionally, people with high socioeconomic status usually have strong will of participating in community activities, which can help strengthen the informal control effect.

Table 1 lists the summary statistics of the streetscape and control variables used in the study.

3.3. Method

This study used the discrete spatial choice model (Bernasco &

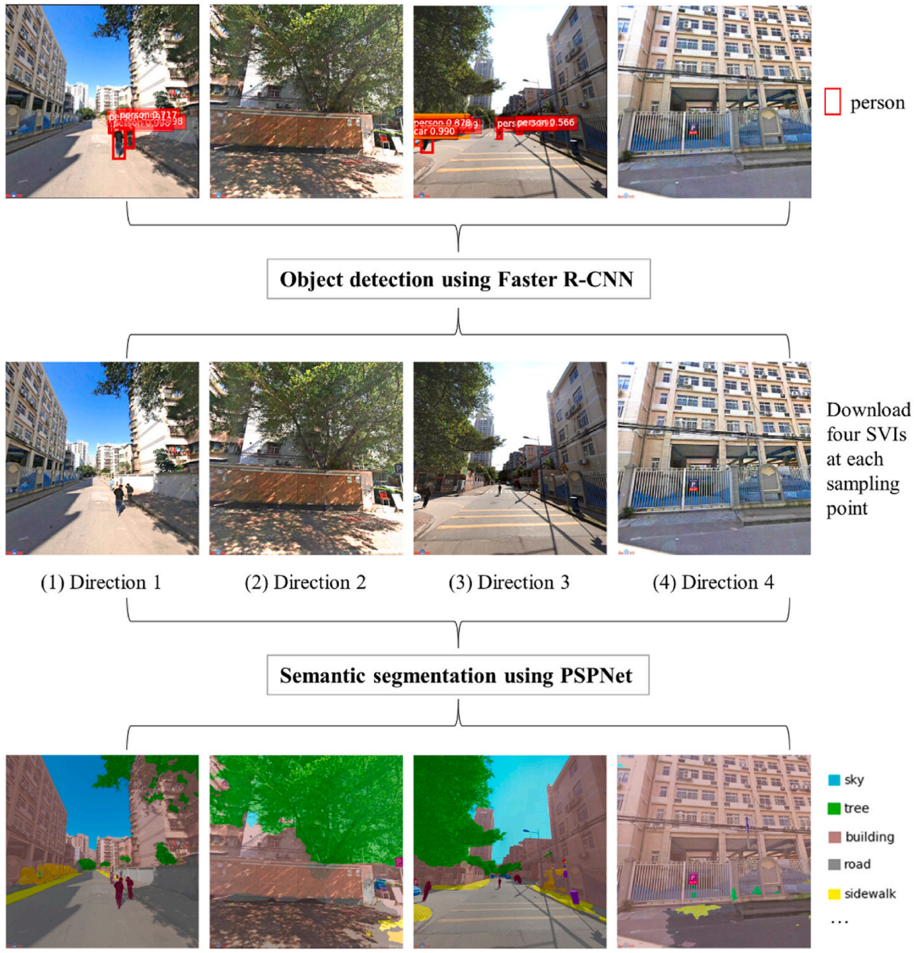

Fig. 5. Detect people on the street using Faster R-CNN and extract the streetscape physical environment features using PSPNet.

Table 1
Summary statistics of community variables.

Variable	Mean	SD	Min	Max	VIF
Streetscape variables					
Number of people on the street (per 1000)	3.425	2.824	0.081	26.133	7.404
Percent wall (%)	3.012	1.408	0.190	16.899	6.517
Percent fence (%)	0.503	0.249	0.033	2.460	4.606
Percent window (%)	0.094	0.060	0.002	0.657	4.202
Percent grass (%)	0.595	0.702	0.001	5.252	2.769
Percent plant (%)	2.101	1.136	0.069	7.748	5.832
Percent sidewalk (%)	2.713	0.927	0.077	6.715	5.625
Crime attractors, generators, and detractors					
ATM and banks (#)	5.229	6.847	0	96	2.896
Bus stops (#)	4.475	5.766	0	104	3.217
Subway stations (#)	0.455	1.409	0	16	1.284
Schools (#)	4.971	5.144	0	34	3.396
Hospitals (#)	1.259	4.143	0	66	1.141
Guard stations (#)	1.479	1.758	0	14	2.000
Socioeconomic features					
Percent migrants (%)	20.599	17.603	0	79.365	3.286
Percent lowly-rent house (%)	71.316	34.065	0	100	5.977

Nieuwbeerta, 2005) to examine how the streetscape environment features and other control variables affect street theft crime offenders' location choices. The research field of crime geography employs a discrete spatial choice model to analyze the factors that influence offenders' decisions in selecting a community j for committing crimes, with the dependent variable being dichotomous. Specifically, it represents whether an offender i has chosen a particular community as the location for committing a crime. In our study, there were 1540 crimes committed across 1636 communities, resulting in a total of 2,519,440 observations. However, only 1540 observations were tagged with a value of 1, indicating the selected communities by corresponding offenders. It should be noted that the number of alternatives available to each offender may differ based on their home locations and range of daily activities. This variability is accounted for by incorporating the residence-crime proximity variable in our discrete choice models, which controls for the effect of offenders' accessibility to each alternative community. Previous studies by Brantingham and Brantingham (2008), Xiao, Ruiter, Liu, Song, and Zhou (2021), and Ruiter (2017) have also utilized this variable in their analyses.

Suppose an offender i selects a community j as the location for committing a crime. In this case, the offender must believe that the chosen community will provide more utility U_{ij} than other potential communities. To determine the offender's perceived utility of community j, we employ the following equation:

$$U_{ij} = \beta_{SVI} SVI_j + \beta_{AGD} AGD_j + \beta_{SEF} SEF_j + \beta_{prox} Prox_{ij} + \varepsilon_{ij} \tag{3}$$

where SVI_j, AGD_j, SEF_j are observed data on streetscape variables, crime attractors, generators, and detractors, and socioeconomic features from each potential target community j. The observed data for the residence-crime proximity variable $Prox_{ij}$ relates to both offender i and potential target area j. The coefficients β_{SVI}, β_{AGD}, β_{SEF} and β_{prox} are estimated using these observed data. In addition, a random term ε_{ij} represents unobserved factors that may affect the utility but are not observed by analysts. The estimated coefficient of each independent variable indicates the direction and strength of the association between the variable and the offender's preference for a location.

According to McFadden's theory of random utility maximization (McFadden, 2001), offenders select targets that provide them with the greatest utility. As a result, the conditional logit model, which is a practical model derived from the theoretical discrete spatial choice model, can be formulated as follows:

$$P_{(Y_i=j)} = \frac{e^{\beta_{SVI} SVI_j + \beta_{AGD} AGD_j + \beta_{SEF} SEF_j + \beta_{prox} Prox_{ij} + \varepsilon_{ij}}}{\sum_{j=1}^{1636} e^{\beta_{SVI} SVI_j + \beta_{AGD} AGD_j + \beta_{SEF} SEF_j + \beta_{prox} Prox_{ij} + \varepsilon_{ij}}} \tag{4}$$

where Y_i represents whether offender i chooses to commit crimes in community j.

Both coefficients βs and odds ratios e^{β}s can be calculated from the results of the conditional logit model. The odds ratio reflects the increase in the probability of a community being targeted by an offender with a one-unit increase in the independent variables. In previous studies (Bernasco & Nieuwbeerta, 2005; Ruiter, 2017; Xiao et al., 2021), odds ratios have been commonly used to explain how the characteristics of potential targets influence offenders' choices of crime locations, rather than using coefficients.

Fig. 6 summarizes the workflow of this study, which majorly includes three steps. (1) Generate sampling points along the street network, based on which we calculate four azimuth angles at each sampling point. Pass the coordinate (longitude and latitude) of a sampling point, azimuth angle, and other parameters like pitch angle, fovy angle, width and height of the image into the BSV API. Collect four BSV images at each sampling point based on the URLs. (2) Detect and count the number of people on the street using an object detection network (Faster R-CNN). Extract and calculate the proportions of wall, fence, window, grass, plant, and sidewalk pixels using a semantic segmentation network (PSPNet). (3) Construct a discrete spatial choice model to determine the influences of on-street population and streetscape physical environment features on street theft crime offenders' crime location choice, controlling for the effects of residence-crime proximity, crime attractors, generators, detractors, and socioeconomic features.

4. Results

Before running the conditional logit model, we calculated all the independent variables' variance inflation factors (VIFs). Results demonstrate that the VIF values are smaller than 10 (shown in the last column of Table 1), the commonly accepted threshold value in discrete choice modeling crime research (Bernasco & Block, 2011). Therefore, the results in this research have no severe multicollinearity issues.

Table 2 presents the estimated model parameters, including odds ratios, confidence intervals, and indicators of statistical significance.

- *Fitting performances of models*

In order to inspect whether the model has a performance improvement after including the streetscape variables, we constructed a baseline model which does not include the streetscape variables. Model 1 is the baseline model without the streetscape variables, while Model 2 is the full model with the streetscape variables. The log-likelihood of Model 2 is −8705.44, which is larger than that of Model 1 (−8788.43). The AIC of Model 2 (17446.9) is smaller than that of Model 1 (17598.87). The

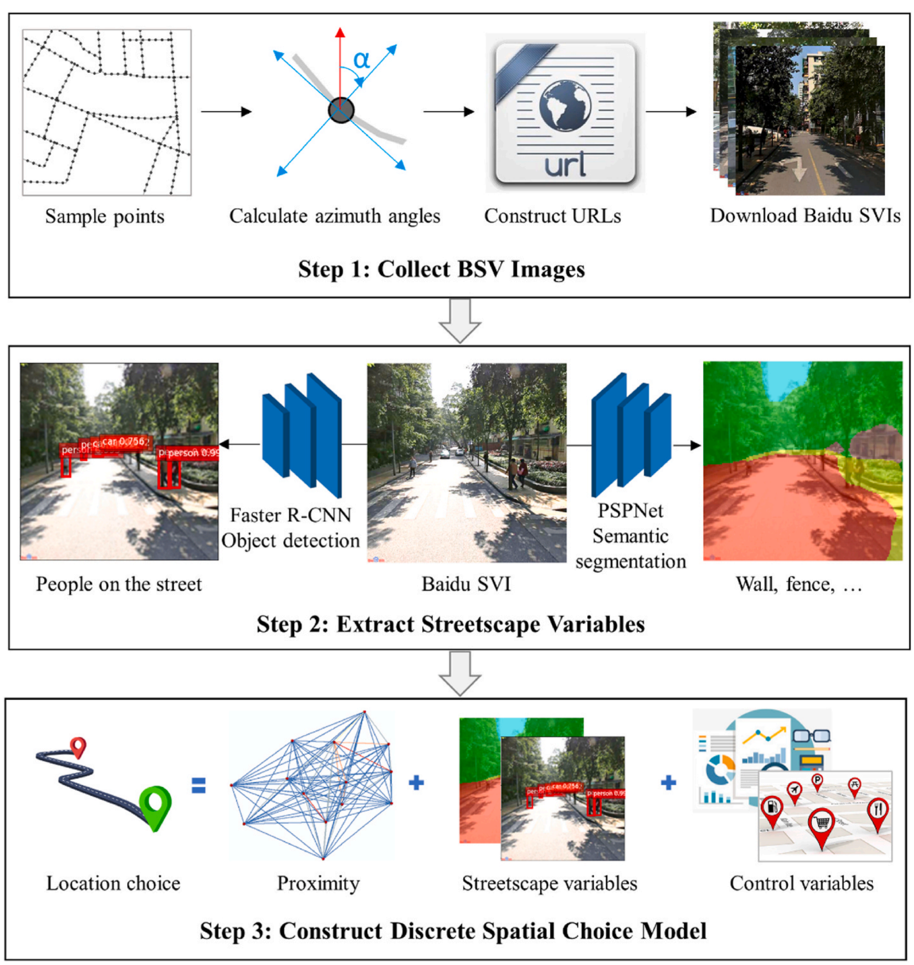

Fig. 6. The workflow of this study.

Table 2
Conditional logit estimation with robust standard errors.

Variable	Model 1			Model 2		
	Odds ratio	95% Confidence interval		Odds ratio	95% Confidence interval	
		Lower	Upper		Lower	Upper
Streetscape variables						
Number of people on the street				1.114***	1.090	1.138
Percent wall				1.019	0.972	1.068
Percent fence				1.367***	1.219	1.532
Percent window				0.966	0.541	1.725
Percent grass				0.869*	0.781	0.967
Percent plant				1.097**	1.036	1.160
Percent sidewalk				0.852***	0.816	0.890
Proximity (km)	1.297***	1.268	1.327	1.295***	1.265	1.325
Crime attractors, generators, and detractors						
ATM and banks	1.011***	1.005	1.017	1.004	0.997	1.010
Bus stops	1.018***	1.013	1.024	1.016***	1.008	1.023
Subway stations	1.055***	1.025	1.084	1.044**	1.014	1.075
Schools	1.044***	1.035	1.054	1.021***	1.009	1.031
Hospitals	1.009*	1.001	1.017	1.002	0.993	1.011
Guard stations	1.011	0.985	1.039	1.003	0.976	1.030
Socioeconomic features						
Percent migrants	1.006*	1.001	1.011	1.001	0.999	1.004
Percent low-rent houses	1.001	0.998	1.002	1.000	0.999	1.001
Log-likelihood		−8788.43			−8705.44	
AIC		17598.87			17446.9	
Pseudo R^2		0.228			0.237	
Likelihood ratio test of model difference (chi-square)			172.43			
Number of crimes			1540			
Number of communities			1636			
Number of observations			2519440			

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

pseudo R^2 of Model 2 (0.237) is larger than that of Model 1 (0.228). Additionally, we conducted a likelihood ratio test on two models. The results indicated a chi-square value of 172.43 (with 7 degrees of freedom), implying a significant difference between the two models. In summary, incorporating streetscape variables can significantly improve the fitting performance of the model. Therefore, on-street population and streetscape physical environment features play an effective role in understanding street theft crime offenders' crime location choices.

To enhance interpretation, Fig. 7 illustrates the conditional logit estimates of Model 2 graphically, presenting odds ratios and 95% confidence intervals. The dots in Fig. 7 denote estimated odds ratios, representing the multiplicative impact of independent variables on the odds that an offender targets a particular community. The horizontal position of a dot represents the direction and strength of the effect, with dots located to the right (left) of the reference value of 1 indicating an increase (decrease) in the probability of a community being selected. The horizontal lines displayed in Fig. 7 represent the 95% confidence interval of estimated odds ratios. Therefore, all effects where these lines intersect or touch the dotted vertical line at value 1 are not statistically significant at $p < 0.05$.

- *Effect of streetscape variables on offenders' crime location choices*

The estimated odds ratio of the number of people on the street in Model 2 is 1.114, demonstrating that the larger the on-street population is in a community, the more likely the community will be chosen by offenders as the place to execute crimes. More specifically, the odds of an offender preferring a community will increase by 11.4% if the community has 1000 more people on the street. Furthermore, the lower and upper bounds of the confidence interval are both above 1 (1.090–1.138). Therefore, the odds ratio of the number of people on the street is statistically significant at $p < 0.05$ (two-sided).

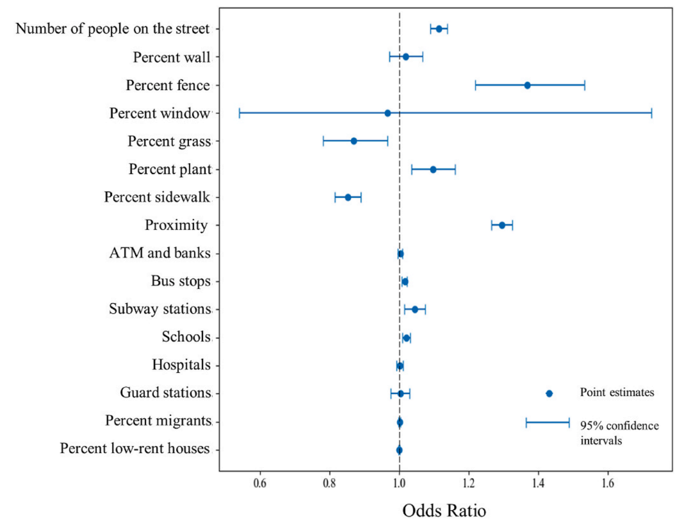

Fig. 7. Conditional logit estimates (odds ratios and 95% confidence intervals) of Model 2.

The estimated odds ratios of percent fence and plant are also positive and statistically significant. The variable of percent wall also has a positive impact on attracting offenders. However, the confidence interval covers 1, which indicates a non-significant influence.

The variables of percent grass and percent sidewalk significantly negatively influence offenders' crime location choices. The variable of percent windows has a non-significant negative impact on the offender's crime location choice.

- *Effect of proximity on offender's crime location choice*

The estimated odds ratio of the proximity effect is 1.297 in Model 1 and 1.295 in Model 2. These results demonstrate that the closer a community is to an offender's home, the more likely it will be chosen by the offender. More specifically, the value of 1.295 implies that the odds of an offender choosing a community will increase by 29.5% if the distance between the community and the offender's home decreases by 1 km.

- *Effect of crime attractors, generators, and detractors on offenders' crime location choices*

According to the results shown in Table 2, the effects of crime attractors and generators on offenders' crime location choices in the two models are roughly consistent. The estimated effects of three types of crime attractors and generators (bus stops, subway stations, and schools) are positive and statistically significant in the two models. The effects of ATMs and banks, and hospitals are statistically positive in Model 1. However, the positive effects are not statistically significant in Model 2.

Compared comprehensively, subway stations exhibit the greatest influence among crime attractors and generators, followed by schools. If a community has one more school, its odds of being chosen will increase by 2.1% (Model 2). Additionally, the odds of offenders preferring a community will grow by 1.6% if the community has one more bus stop.

- *Effect of socioeconomic features on offenders' crime location choices*

Regarding the variable of percent migrants, the odds ratio of 1.006 in

Model 1 reveals a weak positive effect. For the variable of percent low-rent houses, the odds ratios of 1.001 in Model 1 and 1.000 in Model 2 are quite similar and indicate a positive and non-significant effect.

5. Discussion

The findings of the influences of on-street population and streetscape physical environment on street theft crime offenders' location choice are generally aligned with previous studies. The number of people on the street has a significantly positive impact, which means that locations with larger on-street populations are more attractive to criminals. This result coincides with existing theoretical and empirical studies. First, the rational choice theory assumes that criminals are rational people who make choices by weighing potential benefits over the costs and risks of committing a crime (Cornish & Clarke, 1987). Offenders' intentions of committing crimes are often motivated by maximizing potential benefits and minimizing risks and costs (Loughran, Paternoster, Chalfin, & Wilson, 2016). Therefore, as to a location, the lower the cost and risk, and the greater the potential profit, the more likely it is to be chosen by offenders. Places with large on-street populations are such types of locations. On the one hand, the presence of a large number of people on the street provides rich targets and opportunities for offenders. On the other hand, the dense crowd provides cover for offenders. Offenders' surreptitious behaviors of searching for targets and committing offenses are not easy to be noticed. It is also feasible to flee the scene after committing a crime without being spotted. Therefore, locations with dense on-street populations are perfect places for street theft crimes. Second, property crime offenders' preferences for locations with large numbers of people have been demonstrated by existing empirical research. For example, Hipp et al. used Google SVIs and a semantic segmentation network to detect the presence of people on the street (Hipp et al., 2021). Their results demonstrated that more persons in the environment are associated with higher crime levels. Vomfell et al. used social media and other data sources to evaluate population activities (Vomfell, Härdle, & Lessmann, 2018). After controlling the effect of demographic features, their results revealed that population size plays a significant role in predicting the occurrence of property crime. Boivin measured the population flows of residents using transportation telephone survey data (Boivin, 2018). Based on this data, the study investigated the effect of ambient population on crime in Toronto and found that population size positively influences crime in some areas.

The results of this study also reveal meaningful influences of streetscape physical environment features extracted from BSV images on street theft crime offenders' location choices. The variable of percent fence, which means the average proportion of fence pixels in BSV images in a community, shows a significant positive impact on offenders' crime location choices. Percent fence and percent wall are two defensible space measurements. However, percent wall reveals no statistically significant effect on crime location choice in this study. The CPTED and the defensible space literature suggest that some aspects of the environment can encourage or prevent crime events (Newman, 1972). As a critical CPTED feature, fences can limit the accessibility of a place, making it difficult for a potential offender to enter to commit crimes and escape from the place (Hipp et al., 2021). However, according to the results of this study, fences do not exert an inhibiting effect on crime location choice but show a strong attraction to offenders. Fences, such as iron railings, chain links, and pickets, are those we can see through. Although fences make it more difficult to access a location, it does not obstruct offenders' views when they look around, searching for potential targets and guardians. On the other hand, the traffic administration department in China usually put roadside railing along the street to divide pedestrian flow and traffic stream. Streets with more pedestrians usually occupy more roadside railings. These may be the reasons why fences fail to play an inhibiting effect in offenders' crime location choices.

The results of this study reveal that places with plants are attractive to street theft crime criminals. On the contrary, grasses show an inhibiting effect on offenders' crime location choices. As two types of vegetation with distinct heights and shapes, grass and plant have entirely different associations with offenders' preference for crime location. Plants captured by SVIs are low vegetation, like shrubs and floras. The presence of plants may act as a prospect blocker or a hiding place for potential offenders (Lis, Weber-Siwirska, & Ziemiańska, 2016). A previous study has found that dense vegetation could provide opportunities to facilitate committing offenses. Therefore, criminals prefer to use places with dense vegetation (Michael, Hull, & Zahm, 2001). Grasses are low and short plants usually used to cover the ground in lawns and parks. Places with a large grass cover usually have a broad vision, and suspicious people and activities are easily noticed. The natural surveillance effect may thus erode potential criminals' preferences for these locations.

Percent sidewalk has an inhibiting effect on street theft crime criminals' location choices. The reason may be that sidewalks are commonly built along the sides of roads with broad surfaces. Wide roads are generally auto-oriented with low walkability. Therefore, pedestrians may not be likely to travel on these roads. These locations are not attractive to criminals because of the absence of ample opportunities.

The proximity variable presents a large positive association with offenders' choice of crime locations. This result is consistent with previous research, which confirmed that criminals are likely to commit crimes close to their residences (Bernasco & Block, 2009; Bernasco & Nieuwbeerta, 2005; Kuralarasan & Bernasco, 2021; Ruiter, 2017). This finding complies with the crime pattern theory that offenders choose crime locations within their awareness space. Locations near their residences form one of the main constitutional elements of their awareness spaces because they are familiar to the criminals. Therefore, these places are appealing to offenders.

Crime attractors and generators like bus stops, subway stations, and schools attract criminals because they draw large crowds, which provide crime opportunities. Among crime attractors and generators, subway stations reveal the most potent attraction to offenders. The reason may be that subway stations are places with high pedestrian flows. The attraction of bus stops to offenders is relatively weaker than that of subway stations. The reason may be that bus stops generally draw fewer people than subway stations. Schools also appeal to criminals as the parents who gather around the schools to take their children to school or back home are suitable crime targets.

This study has some limitations. Streetscape physical elements like buildings and trees are stationary and stay relatively stable over time. However, the number of people on the street changes with the time of day. Although SVIs have the unique potential to detect people on the street that other data sources do not (mobile phone, social media, taxi trajectory, and other commonly used data sources cannot distinguish between people on the street and indoors), SVIs are limiting because they are collected by street-view cars instantly. They are static and cannot capture the dynamic change of on-street population. Additionally, small objects like broken windows, litter on the street, and graffiti are important signs of physical disorder, which may attract crimes. Future crime location choice research should take these variables into account. Image classification and object detection techniques may be possible solutions to extract physical disorder signs from SVIs. Following the approach of most crime location choice studies in both western and Chinese cities, the alternative set was the same for all offenders (Ruiter, 2017; Song et al., 2019). However, offenders may have different preferences when selecting targets. Future research could narrow down the alternative set for each offender by determining the spatial extent of their daily activities, which may lead to more accurate model results.

6. Conclusions

The present research uses a discrete spatial choice model to investigate the influences of on-street population and streetscape physical environment features on street theft crime offenders' crime location choices. By integrating SVIs and deep learning approaches, this study detects people on the street and fine-grained streetscape physical environment features, including walls, fences, windows, grasses, plants, and sidewalks. To the best of our knowledge, this is the first empirical study examining the association between streetscape conditions and criminals' crime location choices.

Results show a significant improvement in model performance after the streetscape variables are accounted for. Therefore, it is necessary to consider the influence of streetscape context when studying street crime offenders' preferences for crime locations. Regarding the streetscape variables, the number of people on the street significantly positively associates with offender preference. Fences have a significant and positive effect on attracting criminals, which means the failure of this defensible space measure to inhibit the occurrence of crimes. Grasses and plants are vegetations with distinct heights and shapes, revealing opposite effects. Grasses significantly negatively impact offenders' location choices, while plants have a significantly positive impact. Finally, sidewalks demonstrate a significant and negative impact on attracting offenders. Walls and windows show no significant effect on criminals' crime location choices. Additionally, the directions and strengths of the associations between most control variables and offenders' preferences for crime locations are consistent with extant theoretical and empirical research.

This study introduces a practical solution to detect people on the street and fine-grained streetscape physical environment features, which are closely associated with street crimes but are difficult or expensive to extract by traditional methods. Additionally, compared with traditional images gathered from a bird's eye view, SVI is a more human-oriented data source. SVIs thus have an advantage in emulating the actual streetscape environment perceived by pedestrians when they walk through the streets. In conclusion, this study provides evidence that SVIs and deep learning techniques offer us a new opportunity to quantify the streetscape environment in a large region at a low cost, laying a foundation for place-based crime research.

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Author statement

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