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Research Article

Using Street View Images to Examine the Impact of Built Environment on Street Property Crimes in the Old District of CA City, China

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Property crimes on the street are common in cities, posing a certain threat to people's daily life safety and social stability. Therefore, it is essential to analyze the characteristics and spatial patterns of street property crimes in the built environment to make cities safe. Based on environmental criminological theories, this study takes the MC old district in CA City as a case study and uses a negative binomial regression model to analyze the influencing factors of street property crimes in different periods. The results show the temporal and spatial differentiation in street property crimes. In terms of time, the number of crime cases presents the features of "three peaks and two troughs." In terms of space, crime cases show spatial clustering patterns, mainly concentrated in the commercial and prosperous areas where the main roads of the city are located. During the whole day, openness, banks, bars, and restaurants have a significant positive effect on crime occurrence; closeness, police cameras, grocery stores, and distance to the nearest police patrol station had a significant negative effect on crime occurrence. There are two explanations for the positive and negative correlations of some environmental variables with a crime before dawn, daytime, and nighttime. This study explored the spatial-temporal distribution and factors that influence the old district street property crimes by extracting physical environmental characteristics from street view images using deep learning algorithms and providing a reference base for police departments to prevent and combat crime.

1. Introduction

With the accelerating urbanization process, the management problems facing cities have become more complex. Crime has become an important factor that seriously threatens the lives, property, and social stability of citizens. The focus of academic circles is exploring the relationship between urban-built environments and criminal behavior. As one of the branches of criminology, the core of environmental criminology is to focus on the key role environmental factors play in crime and try to control and prevent crime by analyzing and modifying the environment [1]. Modern environmental criminology was introduced in 1971 by the American criminologist C. Ray Jeffery to call for a new school of criminology [2]. While retaining the principles of classical criminology, it shifts the focus from the offender to the environment in which the crime occurs [3].

The classic theories of environmental criminology include Crime Prevention Through Environmental Design (CPTED), Routine Activity Theory (RAT), and Crime Pattern Theory (CPT). Jeffery first proposed CPTED in his work [2]. Moffait then proposed that the first-generation

CPTED concept had six main characteristics: territoriality, surveillance, access control, image maintenance, activity support, and target hardening [4]. This theory contributes to social sustainability by examining the relationship between the environment and behavior to reduce opportunities for crime and reduce risk. RAT assumes that each criminal event requires 3 elements: a potential offender, a suitable target, and the absence of a monitoring subject to stop the crime from occurring. At the microlevel, the lack of crime prevention and security is a situation in which crime may arise from a suspect's contact with a suitable criminal target [5]. CPT assumes that the distribution of crime events is not random but occurs where the activity spaces of offenders and targets intersect [6]. CPT describes the activity space in more detail based on RAT. This theory defines places with many crime opportunities as crime attractions and crime occurrence places and can analyze why crimes are prone to occur in certain areas. It is of positive significance to explain the hotspot of crime in the urban environment. The current theoretical construction of environmental criminology research is becoming more mature, and the research content favors community crime, crime policing and practice, and the construction of crime selection models. From the point of view of research area selection, the old district is densely populated and functionally mixed, but there are fewer studies on microcrime in the old district. How to apply the theory of environmental criminology to the old district and put forward reasonable control countermeasures to inhibit crime is of theoretical significance and practical significance.

With the rapid progress of artificial intelligence and deep learning technology, more and more scholars combine them with street view images and built environment features to explore the microenvironment influence on crime, thus enabling environmental criminology research to focus on a more microscopic scale and providing new perspectives for crime prevention. The complex spatial structure and the interaction and mixing of multiple functions in the old district make their safety management more challenging. The remodeling and construction of the environment is an important opportunity to create a safe urban environment. Based on sorting out the research progress of environmental criminology, conducting security research for the old district is expected to enrich and expand the use of environmental criminology theories for the old district. It is of positive significance to verify and discuss the rationality and applicability of the relevant theories on the influencing factors of crime and its causes. Therefore, based on CPTED, RAT, and CPT, this research takes the old district of MC in CA City as a case site and the property crime cases that occurred on the street as the research object. After extracting the physical characteristics of the environment from the street image using the FCN visual image semantic segmentation algorithm together with POI data as the characteristics of the built environment of the study area, we use mathematical modeling around two dimensions of spatial and temporal to analyze spatial and temporal patterns and the factors influencing the property invasion crimes on the street under multiple time scales.

2. Literature Review

2.1. Crime and Built-Environment Research. Street crimes refer to crimes committed by offenders in public spaces, such as streets, through physical contact with victims, and the main types of crimes include robbery, snatching, theft, and intentional injury. Yue et al. believe that the current street property crimes mainly focus on the 3 types of robbery, snatching, and theft. They studied how street crime is influenced by the number of people on the street and the construction of the street view and found that the percentage of buildings and trees showed a significant negative correlation with crime occurrence [7]. Using urban facility nodes as research data for criminal behavior research yields results closer to the objective patterns of actual occurrence. More and more scholars are using RAT to study the effects of different types of urban facilities on the occurrence of criminal behavior [8]. Research in the field of environmental criminology incorporates the physical environment in the study of factors that affect crime occurrence, and the selection of element nodes includes bars, liquor stores, parks, convenience stores, schools, and other places [9, 10].

The old district has many service industries, such as urban entertainment, leisure, and catering, with a high number of street property crimes. These place nodes are spatial carriers of people's daily life. Their internal and neighboring spaces usually gather a large number of people, which provides crime targets for offenders and increases the risk of crime in these nodal elements [11, 12]. Gruenewald and Remer studied cross-sectional data on violent crimes in California in 6 years and found that an increase of 10% in the number of stores and bars would increase the violence in the backward areas of the local area by 1.67% and 2.06%, respectively [13]. By studying violent and property crime in 9 US cities, Wo concluded that liquor stores and banking institutions increase crime opportunities and are typical crime attractors [14]. Ergun and Yirmibeşoğlu evaluated the distribution of crime in Turkey's largest city and found that crime rates were higher in the districts that were older and closer to the center [15]. Research on public space safety in the field of community and urban planning has mainly focused on human element evaluation and physical space planning. Empirical research, represented by American scholars, has achieved notable results in social practice in several Western countries. The crime phenomenon that exists in the process of urbanization makes urban residents' demand for urban security and safety increase. Currently, the spatial scale of urban crime research is gradually changing from macro to micro, and the study of the relationship between crime and the environment on the microscale can play a positive role in crime prevention and control.

In studying the relationship between elements of the old district built environment and criminal behavior, elements of points of interest (POI) nodes, including restaurants, commercial, and entertainment facilities, can describe the built environment at the urban microscale. These places attract a large number of people in their daily lives and become typical places where crime is attracted and crime occurs [14, 16, 17]. Exploring these elements can help reveal the relationship between the built environment and crime in the old district. Formal surveillance formed by nodal elements such as police cameras and police stations reflect the soundness and effectiveness of regional security. These facilities have a certain crime prevention effect and a deterrent effect on the psychology of potential offenders, which can reduce the opportunities for crime, increase the cost of crime, and enhance the sense of security of nearby residents. But the relationship between their crime-inhibiting effect and time period still needs to be further explored [18].

2.2. Crime Visual Analysis Research. Visual perception dominates human perception of space [19]. With the widespread coverage of street view data and the emergence of urban visual spaces, street view data have recently gained great attention in urban space research [20]. Street view data have become one of the most intuitive, accurate, and effective ways to observe the environment and assess perception. Common data sources are provided by map companies, including Google Street View (GSV) and Baidu Street View (BSV). Researchers can use these companies' Application Programming Interfaces (APIs) to obtain static street view images from these institutions to extract high-resolution photos of streets and neighborhoods that reflect the visual environment as seen by residents [21, 22]. An urban street view has been launched in many countries and cities around the world. Because of its wide coverage and high accuracy, it has become a rapid collection of high-precision street data. It can be used as a data source for analyzing urban environments and measuring the safety and quality of street spaces [23–25].

With the rapid development of computer technology, the use of deep learning is becoming more and more common. More scholars are using deep learning to study the urban street environment and analyze the environment at the level of visual perception [26, 27]. Since AlphaGo, developed by Google's DeepMind team, defeated the human world champion, artificial intelligence and deep learning techniques have gained greater attention, with research applications including the use of deep learning techniques to extract visual semantic features from images rapidly [28]. Early methods for extracting semantic features from images mainly identified objects by the color of pixels in the image. But when there are two different object colors in the image, the objects have similar colors, or there are rare objects in the image, this method has obvious defects, and it is not easy to complete the visual analysis [29]. In recent years, scholars have used deep convolutional neural networks to process visual information in images using deep learning algorithms such as fully convolutional networks (FCN), ResNet, and SegNet. These algorithms can identify various visual features in images, such as lanes, buildings, sky, sidewalks, trees, and greenery, laying a solid foundation for more reliable research on urban street quality and visual perception [30–34].

Yao et al. proposed a human-machine adversarial scoring framework based on deep learning. This framework used a random forest-based module to explore the relationship between street view elements and user scores. It can collect street view scores from residents who understand different perception standards. This framework can be used to study the link and correlation analysis between street visual characteristics and resident perceptions [35], using this deep learning human-machine adversarial scoring framework to classify perceptions of the streetscape into six dimensions: beautiful, wealthy, safe, lively, depressing, and boring. Positive perceptions were positively correlated with the presence of plants and roads, negatively correlated with walls, ground, water, and fences, and negative perceptions were positively correlated with walls and buildings [25]. The visual enclosure and traffic flow both increased the perceptions of residents of safety, and the perceptions of residents of danger would be reduced in areas with high traffic and pedestrian flow and complete safety facilities, and the green perceptions would decrease the perceptions of residents of safety, suggesting that areas with dense trees may enhance the perception of danger [36]. By examining the relationship between urban streetscapes and perceptions of safety, Harvey et al. found that streetscapes consisting of a large tree canopy, numerous free-standing buildings, and fences with large cross-sectional proportions were considered the safest, with trees having a greater positive effect on perceptions of safety than building-related streetscape variables [20]. These studies have shown that calculating Greenness, Closeness, and other metrics of street view images through computer vision analysis can quickly and efficiently explore the relationship between street view and safety. However, these types of studies did not take the actual crime data and urban POI data as variables and only investigated the subjective visual perception of the streetscape.

Street view imagery can quantify the impact of the street-built environment on crime occurrence and provide useful information on urban street view design for crime prevention [37]. Yue et al. evaluated visual elements such as trees, buildings, and streets in the streets to explore the relationship between these variables and crime using a deep learning full convolutional image segmentation algorithm. The areas with many trees were found to be more prone to public theft, and areas with many roads and sidewalks were less prone to public theft [7]. However, other studies have suggested that greener areas increase the number of visits by residents and that this increased natural surveillance reduces crime [22, 38–40]. The access control concept of CPTED theory suggests that crime cases are positively correlated with Openness and negatively correlated with Closeness [4]. A related study concluded that closed and vegetated urban spaces lead to higher levels of fear of crime [39]. It has been shown that an increase in the amount of sky in the streets promotes the openness of the public space and thus a reduction in crime [38].

The relationship between roads and crime is controversial in previous studies, and studies by different scholars have concluded that roads can inhibit crime [41], promote crime [22, 38], and have an insignificant relationship with crime [7]. Luo et al. used a deep learning model to analyze urban street view images to reveal the relationship between urban environmental variables and street crime. The study found that different variables of the geographical environment had different degrees of potential interaction effects on the frequency of street crime [38]. As typical geotagged data, Street View images show great potential in quantifying the relationship between the built environment and criminal activities. He et al. developed an environmental audit approach using GSV to explore the relationship between the residential built environment and violent crime, validating Social Disorganization Theory (SDT), RAT, and Broken Window Theory (BWT) [42].

It can be seen that using the street view as a data source to study the urban-built environment can discover the relationship between different visual elements on urban residents' safety perception and crime situation. The advent of computerized street vision analysis has provided the feasibility of quantifying vision indicators on a large scale. However, judging from the progress of existing research work, it is evident that different studies may not reach the same conclusions. There is a lack of research that combines the built environment of the old district with street view images to explore the factors influencing the cases of street property crimes. The built environment of the old district is very slowly updated, making it more suitable for the use of street photos, which are collected over a longer period of time, to represent the built environment of the old district. Therefore, this study wishes to explore the relationship between Greenness, Closeness, Openness, Road coverage, and crime in older neighborhoods, particularly how different periods affect the metrics. Research results help improve the safety and sustainable development of old urban street spaces.

3. Study Area, Data, and Methods

3.1. Study Area. The study area is located in the old district of MC in CA City, China. (Under the terms of the confidentiality agreement, we cannot reveal the true name.) CA City is located in the central and western parts of China. It is a central regional city, a famous historical and cultural city, and a key tourist city in China. This study selects the old district part of the MC district, with an area of about $3.24\,\text{km}^2$, 20 communities, and a population of about 100,000. As the old district of the city, it has an older built environment, a mix of residents and short-term tenants. It has many service industries, such as urban entertainment, leisure, and catering, with a high number of street property crimes, which are of key concern to the local government and public security departments, and is a typical study area of crime in the old district research.

3.2. Data. The data in this study include street property crime data, road network data, POI data, and street view image data.

3.2.1. Crime Data. The crime data were provided by the public security department of the city of CA. It contains the cases of property invasion that occurred on the street in the study area from January 2020 to May 2022, and the data contain a total of 212 pieces of information on the type of incidents, the location of the crime, the time of the crime, etc. Cases include theft, robbery, snatching, and fraud, and the cases are mainly based on theft.

3.2.2. Road Network and POI Data. The road network and POI data come from the navigation data of the map company in 2022, and the POI data mainly include catering, retail, financial, and leisure and entertainment facilities. In addition, the spatial distribution data of the police patrol stations and the police cameras in the research area are determined by field research.

3.2.3. Street View Data. Street view images are the main source of data in the study. Baidu Maps (https://map.baidu.com/), as one of the largest online map service providers in China, can provide street view images from different angles. According to the data of the research area's road network, the street view photos taken in the summer of 2016–2020 were obtained using the BSV API, and the distance between each of the two sampling points was set to 30 m, a total of 970 sampling points. A total of 3880 street view images were obtained from each sampling point in 4 directions (0°, 90°, 180°, and 270°), with a resolution of 716×358 pixels (Figure 1).

3.3. Methods. Referring to previous empirical research on environmental criminology and the survey on actual police work requirements [8, 43, 44], the research area was divided into 132 grids of $150\,\text{m} \times 150\,\text{m}$. Based on RAT, the time characteristics of street property crimes were analyzed. ArcGIS was used to generate the kernel density map of the spatial distribution of crimes in different periods [5]. Then used, the FCN visual image semantic segmentation algorithm extracts the environment's physical characteristics to construct the visual perception index on the acquired BSV image. Combining POI data with visual perception indicators, negative binomial regression analysis is used to quantitatively discuss the factors influencing street property crime (Figure 2).

3.3.1. Image Semantic Segmentation Based on Deep Learning. To extract effective information from street view images and construct visual perception indicators, this study uses a fully convolutional image segmentation method to perform semantic segmentation on acquired BSV images. The street view images of the study area were first acquired, and then the street view photos were analyzed using FCN-8 deep learning FCN visual image semantic segmentation trained on the ADE20K dataset by Yao et al. The area weight of different semantic objects was subsequently obtained [35]. Among them, FCN-8s are capable of recognizing different objects in street view images [45]. Taking street view images as input, the convolutional layer extracts image elements, the pooling layer can reduce the dimension of the data, and FCN-8s can obtain high-precision semantic segmentation results.

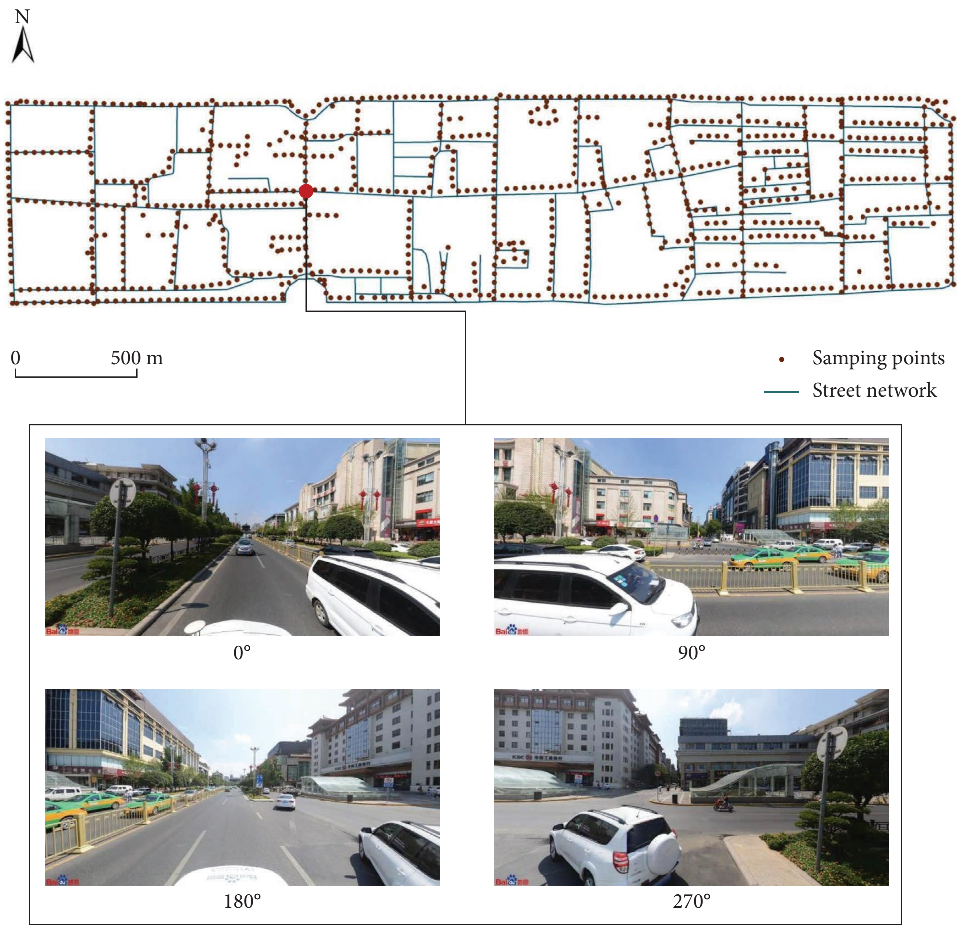

Figure 1: Street view data distribution and angle diagram.

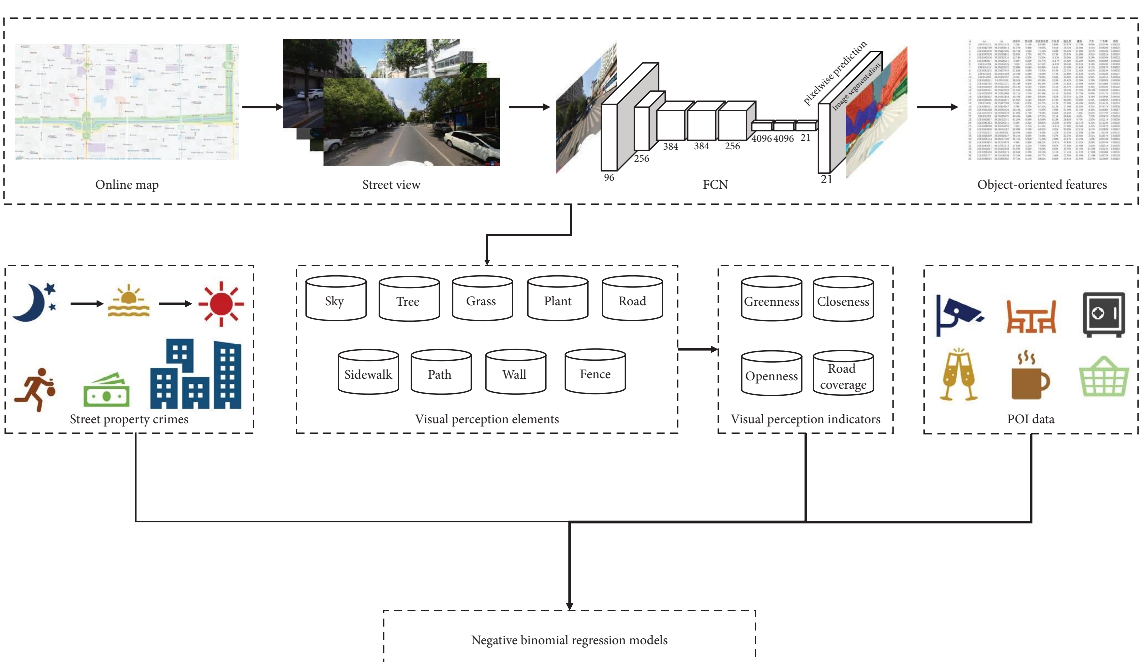

Figure 2: Analytical framework of the factors influencing the characteristics of the built environment and street property crime.

This study uses the ADE20K annotation dataset, which includes 151 categories (trees, buildings, cars, etc.) [46]. By inputting the street view image into the fully convolutional network, the pixel ratio of different objects in the image can be obtained, as shown in Figure 3, the left column is the street view photo, the middle column is the segmented image, and the right column is the superimposed realistic effect. According to the representative elements of visual perception that appeared in previous studies and the most frequent elements of visual perception in street view images [19, 21, 36, 43, 47], this study selected nine categories of visual perceptual elements, including wall, sky, tree, grass, plant, road, sidewalk, path, and fence. After calculating the scores of visual perceptual elements in 4 directions (0°, 90°, 180°, and 270°) for all sampling points, a multicollinearity test was performed to measure the validity of the selected metrics. The results showed that the Variance Inflation Factor (VIF) of each independent variable was less than 5, so there was no serious multicollinearity between the variables.

After determining the percentage of 9 types of visual perceptual elements contained in street view images in 4 directions at each data point, 4 visual perceptual metrics, such as Greenness, Closeness, Openness, and Road coverage, were chosen to be extracted by calculation based on previous studies [19, 36, 48].

(1) Greenness. Green vegetation is an important part of the urban ecosystem and can positively impact people's emotions and psychology. The visual ratio of trees, grass, and plants can reflect the greenness distribution of the city. Figure 4 is an example of greenness.

$$S_k = \frac{1}{n}\sum_{j=1}^{n} H_{jk} + \frac{1}{n}\sum_{j=1}^{n} I_{jk} + \frac{1}{n}\sum_{j=1}^{n} J_{jk},\{j \in (1,2,\ldots,n), k \in (1,2,\ldots,m)\}. \tag{1}$$

In the formula, H_{jk} represents the percentage of tree pixels, I_{jk} represents the percentage of grass pixels, J_{jk} represents the percentage of plant pixels, and the sum represents the total amount of greenness of each street view data point.

(2) Closeness. Closeness refers to the degree to which the street environment closes people's sight and senses, and the pixel ratio of wall and fence in street view images reflects the closeness.

$$T_k = \frac{1}{n}\sum_{j=1}^{n} E_{jk} + \frac{1}{n}\sum_{j=1}^{n} O_{jk,}\{j \in (1,2,\ldots,n), k \in (1,2,\ldots,m)\}. \tag{2}$$

In the formula, E_{jk} represents the percentage of wall pixels, O_{jk} represents the percentage of fence pixels, and the sum represents the total closeness of each street view data point. Figure 5 is an example of closeness.

(3) Openness. Openness is the visibility of the sky in the street that determines the degree of visual openness.

$$V_k = \frac{1}{n}\sum_{j=1}^{n} G_{jk,} \quad \{j \in (1,2,\ldots,n), k \in (1,2,\ldots,m)\}. \tag{3}$$

In the formula, G_{jk} represents the percentage of sky pixels, and the sum represents the total amount of openness of each street view data point. Figure 6 is an example of openness.

(4) Road Coverage. Road coverage is the proportion of all traffic-accessible roads in a street that are covered and provides a sense of the extent of road coverage in the city.

$$X_k = \frac{1}{n}\sum_{j=1}^{n} K_{jk} + \frac{1}{n}\sum_{j=1}^{n} L_{jk} + \frac{1}{n}\sum_{j=1}^{n} M_{jk,}\{j \in (1,2,\ldots,n), k \in (1,2,\ldots,m)\}. \tag{4}$$

In the formula, K_{jk} represents the percentage of road pixels, L_{jk} represents the percentage of sidewalk pixels, M_{jk} represents the percentage of path pixels, and the sum represents the total amount of road coverage of each street view data point. Figure 7 is an example of road coverage.

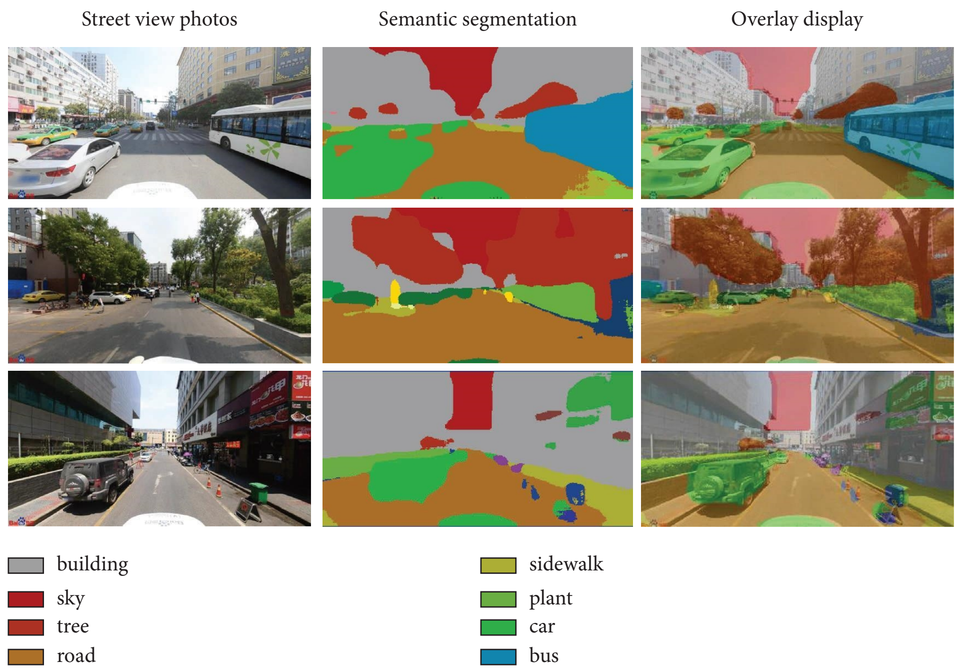

Figure 3: Example of the semantic segmentation effect of street view photo.

Figure 4: Example of greenness.

Figure 5: Example of closeness.

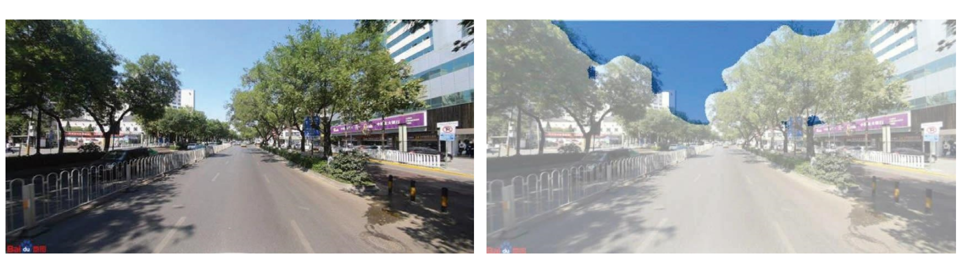

Figure 6: Example of openness.

Figure 7: Example of road coverage.

3.3.2. Negative Binomial Regression Model. The data on street property crimes are over dispersed, which does not meet the requirements of the linear regression model for the normal distribution of the dependent variable. For count variables, the Poisson regression model or negative binomial regression model is often used, but criminal cases usually show statistical overdispersion; that is, the variance is greater than the mean. The negative binomial regression model is a continuous mixed Poisson distribution. Compared to the Poisson regression model, it has a better fitting effect when fitting variables over dispersed [38, 44]. Therefore, the negative binomial regression model is used to analyze the factors of the built environment of street property crimes, and the expression of the probability density function of the negative binomial distribution can be expressed as

$$\operatorname{pr}(Y = y \mid \mu, \alpha) = \frac{\Gamma\left(\alpha^{-1} + y\right)}{\Gamma\left(\alpha^{-1}\right) + \Gamma(y+1)} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu}\right)^{\alpha^{-1}} \left(\frac{\mu}{\mu + \alpha^{-1}}\right)^{y}. \tag{5}$$

In the formula, Y is the dependent variable, the number of street property crimes in the study area; Γ is the Gamma integral, which sets the factorial of the integral parameter; $\mu = E(y)$ is the expectation function; α is the variance parameter of the Gamma distribution; and when α tends to 0, there is no excessive dispersion problem in the data, and the negative binomial model becomes a Poisson model. When α is significantly greater than 0, the negative binomial regression model is a better fit for the data. The marginal effect of the model explanatory variable is called Incidence Rate Ratio (IRR), which indicates that when the explanatory variable x increases by one unit, the average number of events will be IRR times the original number.

3.3.3. Variable Selection. In this article, the number of street property crimes was used as the dependent variable, and four sets of negative binomial regression models were constructed based on a whole daytime (0:00–23:59), before dawn (0:00–6:59), daytime (7:00–17:59), and nighttime (18:00–23:59), and the descriptive statistics of the variables are shown in Table 1. The independent variables of the study are street view, formal social control, and built-environment variables, among which the street view variables are Greenness, Closeness, Openness, and Road coverage. Formal social control variables in the study area include the distance to the nearest police patrol station and the police camera. The former is the Euclidean distance/km between the center point of each cell grid and the nearest security post, police station, and police office. The value of this item is 0 if there are police patrol stations in the grid; the latter is the number of police cameras in each cell grid. The POIs in the built-environment variables are the number of such facilities in the unit grid, among which restaurants and bubble tea and cafes belong to catering facilities, convenience stores, and grocery stores belong to retail facilities, banks belong to financial facilities, and bars belong to leisure and entertainment facilities. After analysis, the VIF of all independent variables is less than 3, and there is no serious multicollinearity between the variables, which can be used to fit the model simultaneously [7, 49].

4. Results

4.1. Spatial-Temporal Distribution Tendencies of Street Property Crimes

4.1.1. Temporal Distribution Tendencies. The number of street property crimes varied significantly with time and, combining the actual situation of the study data with the research of previous scholars [50], each day was divided into 3 time periods: before dawn (0:00–6:59), daytime (7:00–17:59), and nighttime (18:00–23:59). There were 101 crimes before dawn, 76 crimes during the daytime, and 35 crimes at nighttime. As can be seen in Figure 8, the overall number of crime cases shows "three peaks and two troughs," with the highest number of cases occurring at 2:00 a.m., followed by a second peak at 8:00 a.m., then the lowest number of cases, a third peak at 13:00 a.m., then a second low at 14:00 a.m., and then a steady number of cases at night.

It can be seen in Figure 9 that there are significant differences in the number of street property crimes between working days and rest days. On working days, the number of crimes on Tuesdays and Wednesdays increased significantly, with the average daily number of crimes exceeding 35. Thursday had the lowest number of crimes, with 22 cases. The number of crimes on Sunday was significantly higher than on Saturday, reaching 33 cases.

4.1.2. Spatial Distribution Tendencies. Using the Kernel Density Estimation (KDE) in ArcGIS to analyze the spatial distribution characteristics of street property crime cases and obtain the spatial distribution characteristics of crime cases in different periods (Figure 10). It can be seen that street property crimes show the characteristics of spatial agglomeration in all periods. In the KDE of the whole day,

Table 1: Descriptive statistics of dependent and independent variables.

Variable category	Variables	Mean	Std. dev.	Minimum	Maximum	VIF
Dependent variables	Number of crimes for whole day (0:00–23:59)	1.61	2.43	0	15	—
	Number of crimes for before dawn (0:00–6:59)	0.77	1.59	0	9	—
	Number of crimes for daytime (7:00–17:59)	0.58	1.04	0	5	—
	Number of crimes for nighttime (18:00–23:59)	0.27	0.65	0	4	—
Street view variables	Greenness (%)	0.16	0.09	0	0.36	2.68
	Road coverage (%)	0.22	0.08	0	0.36	2.70
	Closeness (%)	0.04	0.03	0	0.18	1.48
	Openness (%)	0.05	0.05	0	0.28	2.32
Formal social control variables	Distance to the nearest police patrol station/km	0.23	0.12	0.01	0.53	1.23
	Police camera	2.30	1.65	0	9	1.36
Built-environment variables	Restaurant	9.05	11.11	0	53	2.37
	Bubble tea and cafe	1.52	2.37	0	14	1.61
	Convenience store	3.15	2.88	0	12	1.99
	Grocery store	1.08	2.75	0	21	1.38
	Bank	0.24	0.58	0	4	1.14
	Bar	1.25	2.38	0	15	1.34

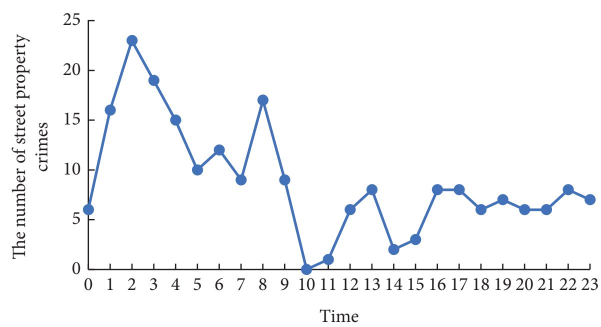

Figure 8: Volume of street property crimes for each hour.

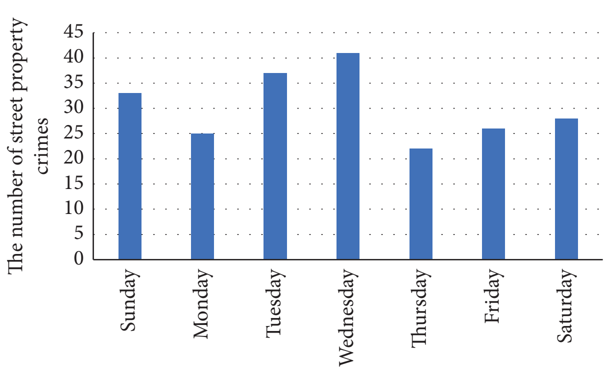

Figure 9: Intraweek pattern of street property crimes.

crime cases are mainly concentrated in the B2-4 and A4-5 areas in the central and western parts of the study area, and residential areas dominate the east side of the study area, and the overall crime cases are lower, showing sporadic characteristics. Before dawn, crime cases are mainly concentrated in the B2, B4, and A5 areas, where B4 is a busy commercial area and A5 is a famous commercial pedestrian street in the old district. There are a large number of bars and restaurants in these three areas, which have a large flow of people and provide criminal opportunities for property crimes. During the daytime, crime cases are mainly concentrated in areas C1, B2-3, and A4-5. These areas are located on the main roads of the city, and the commercial facilities are more attractive. At nighttime, crime cases are concentrated mainly in A4, B4, and C4. These areas not only contain the city's main roads but also have a large traffic flow, and because they are connected to the city's iconic attractions, the lights at night attract more pedestrians to stop and take pictures.

4.2. Factors Influencing Street Property Crimes. Based on the spatial-temporal distribution of street property crimes in the study area, negative binomial regression models were developed separately to analyze the factors influencing crime cases in 4 time periods: whole day, before dawn, daytime, and nighttime. The results of the analysis are shown in Table 2, where B is the regression coefficient and IRR is the incidence rate ratio. There are differences in the Akaike Information Criterion (AIC) values in the 4 models; the fitting effect of the same variable in the 4 time periods is different, indicating that it is necessary to conduct research on street property crimes in different periods [44]. The AIC of models 2, 3, and 4 are smaller than that of model 1, indicating that the construction of a time-phased street property crime model is more effective relative to the overall model for the whole day. It can be seen from the

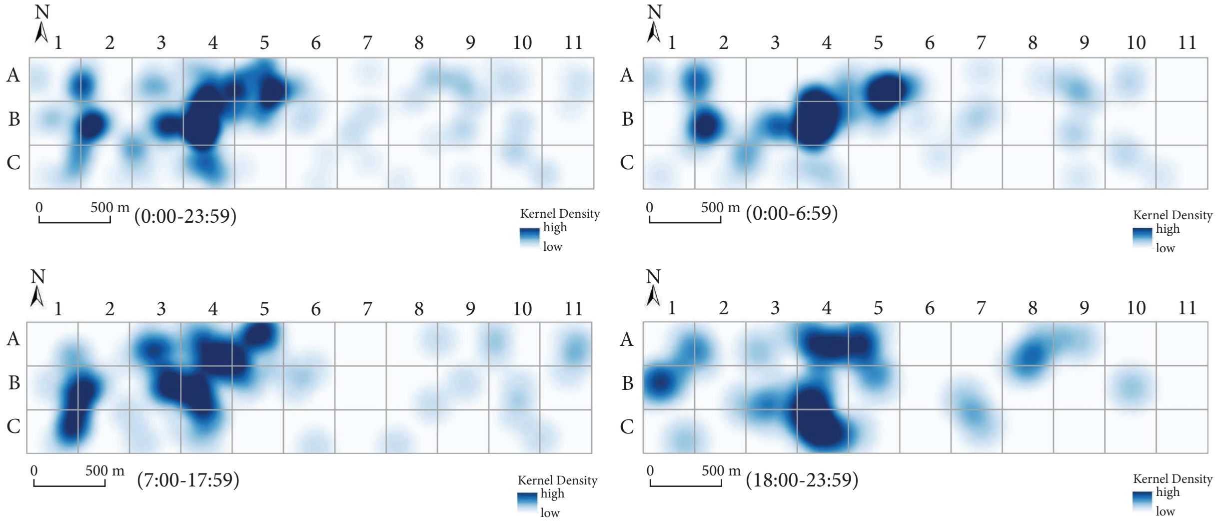

FIGURE 10: Spatial distribution tendencies of street property crimes.

TABLE 2: Negative binomial regression results.

Variables	Model 1: whole day		Model 2: before dawn		Model 3: daytime		Model 4: nighttime	
	B	IRR	B	IRR	B	IRR	B	IRR
Greenness	−0.14	0.87	−0.77**	0.46	0.23*	1.25	−0.55**	0.32
Road coverage	−0.13	0.88	0.47**	1.60	−0.26*	0.77	0.393**	1.48
Closeness	−0.21*	0.81	−0.44*	0.65	0.86**	1.37	0.245**	1.28
Openness	0.60**	1.82	0.02	1.02	0.63**	1.82	0.27*	1.31
Distance to the nearest police patrol station	−0.21**	0.81	−0.19*	0.83	−0.20**	0.82	−0.514**	0.60
Police camera	−0.21*	0.81	0.13	1.14	−0.60**	0.55	0.19**	1.22
Restaurant	1.02**	1.59	0.99**	1.72	0.97**	1.52	0.08**	1.09
Bubble tea and cafe	−0.03	0.97	0.22	1.25	−0.96**	0.38	0.37**	1.45
Convenience store	0.01	1.01	−0.24*	0.78	0.14**	1.13	−0.01	1.00
Grocery store	−0.61**	0.54	−0.39**	0.67	−0.86**	0.76	−0.53**	0.59
Bank	0.50**	1.64	−0.03	0.97	0.53**	1.62	0.43**	1.14
Bar	0.40**	1.50	0.81**	2.26	0.01	1.01	0.13**	1.14
AIC	2557.10		2245.38		2077.76		1995.96	
N	212		101		76		35	

Significance level marks: "*": $p < 0.05$; "**": $p < 0.01$.

calculation that the chi-square value of the likelihood ratio of each model is significantly greater than 0, $p < 0.001$, indicating that the model is effective, and the data are suitable for regression analysis of negative binomial distributions.

In model 1, the variables that significantly relate to street property crimes include closeness, openness, and distance to the nearest police patrol station, police cameras, restaurants, grocery stores, banks, and bars. Among them, openness, restaurants, banks, and bars will have a significant positive impact on the number of crime cases; the closeness, distance from the nearest police patrol station, police cameras, and grocery store will have a significant negative impact on crime. The police cameras in formal social control variables can better suppress the occurrence of property crimes and act as a deterrent to potential criminals. For every additional police camera, the crime rate will drop by 19%. In the street view variables, crime is positively correlated with openness and negatively correlated with closeness, which is consistent with the definition of the two calculated indicators and with the concept of "access control" in CPTED [4]. Among the variables of the built environment, restaurants, banks, and bars were positively correlated with crime occurrence as crime attractors [11, 13, 14]. The high number of residents in the vicinity of grocery stores creates a certain amount of natural surveillance, which serves as a crime deterrent. Potential offenders, as fresh faces in the area, are easily recognized by residents, and thus discourage the idea of committing crimes near grocery stores. For each additional grocery store, the number of property crime cases will be reduced by 46%.

In model 2, road coverage, restaurants, and bars significantly positively affect the number of crime cases, indicating that most street property crimes that occur before dawn are located near restaurants and bars with wider roads nearby. Residents out before dawn mostly go home after eating or go to bars to participate in entertainment activities. Under the influence of alcohol, people's awareness of prevention decreases. In RAT, in the absence of crime prevention and security, potential offenders can commit crimes when they come into contact with suitable criminal targets, increasing the risk of being victimized before dawn [5]. For each additional bar in the study area, the crime increased by 126% before dawn. Before dawn, there are a large number of property crimes around bars, and bars have a greater impact on crimes. Greenness, closeness, and distance to the nearest police patrol station, convenience stores, and grocery stores significantly negatively affected crime. Most convenience stores in the study area are open 24 hours a day, and the convenience stores have large glass windows, which, together with the bright interior lighting, can provide some natural surveillance effect on the adjacent sidewalks. The improvement of greenness and closeness significantly negatively impacts the occurrence of crime. During periods of poor light, people visit areas with higher levels of closeness less frequently. At the same time, areas with a higher greenness can increase the number of visits by residents, and the increased natural surveillance reduces the incidence of crime [22, 38–40].

In model 3, greenness, restaurants, openness, banks, closeness, and convenience stores significantly positively affect the number of crime cases. Among them, greenness, closeness, and convenience stores have the opposite effect on crime occurrence as before dawn. Related studies have concluded that enclosed and vegetated urban spaces lead to higher levels of fear of crime [39] and that the leafy street trees on both sides of the roads within the old district have a stronger effect on light blockage during the daytime, leading to shaded views, which may explain the positive correlation between greenness and closeness and the number of crimes. Convenience stores, banks, and restaurants during the daytime are typical crime attractors and crime generators, contributing to the occurrence of crime [8], and for each additional convenience store, the number of property crimes on the street during the daytime will increase by 13%. Road coverage, distance to the nearest police patrol station, police cameras, bubble tea and cafes, and grocery store can significantly affect the number of crimes. Bubble tea and cafes are more often openly operated, with tables and chairs near the stores for customers to use. People dining, lounging, and lining up are natural surveillance, which inhibits crime occurrence. Road coverage reflects the proportion of street-level roads, with higher coverage having a higher carrying capacity for traffic and pedestrian flow, and with each percentage point increase, the number of crimes decreases by 33%. The fact that bars are closed during the daytime does not affect the occurrence of crime.

In model 4, openness, police cameras, restaurants, bars, closeness, banks, road coverage, and bubble tea and cafes significantly positively affect the number of crime cases. Compared to the daytime, people spend more time in restaurants after work at 18:00, increasing the number of people gathered near restaurants and providing more opportunities for criminals to commit crimes. As an entertainment place that starts business at nighttime, the bar is usually open before dawn the next day. The dim light under the influence of alcohol reduces the awareness of prevention and is prone to property crimes. Most of the customers in the bubble tea and cafes at nighttime are takeaways, and the flow of people gathered near the drink pick-up place provides a suitable target for criminals. The impact of police cameras on crime has changed from a negative suppression during the daytime to a positive effect at nighttime. The reason may be that the police cameras are located in areas with a lot of traffic, and there are more crimes at night. At the same time, police cameras can be poorly and inconspicuously photographed at night when the light is dim, providing a reduced deterrent effect on potential offenders [18]. The greenness and distance to the nearest police station and grocery store significantly negatively affect the number of crimes. Areas with a high level of greenness attract more pedestrians at night, deterring potential offenders [40].

5. Discussion

5.1. Discussion on Experimental Findings. In this research, we explored the relationship between property crimes that occurred on the old district street in different time periods and independent variables such as street view, formal social control, and built-environment variables. Among the variables selected in this study: openness, banks, bars, restaurants, grocery stores, and distance to the nearest police patrol station, there is only one interpretation of positive or negative correlations with crime cases in all periods. In previous studies, banks, bars, and restaurants, as attractions and occurrences of crime, will increase the possibility of crime in the area [8, 11, 12, 14, 51, 52], which is consistent with the results of this study. As nighttime entertainment venues, bars are typically open until early the next morning. Dim lights, loud music, gathering crowds, and unfamiliar surroundings under the influence of alcohol reduce patrons' awareness of prevention and make it easy for property crime to occur. However, the periods in which these three built-environment variables in the old district positively correlate with crime differ. The normal business hours of banks are during the daytime, and some users choose to access cash through Automated Teller machines (ATMs) after work at 18:00. This research found that banks are significantly positively associated with crime during the daytime and nighttime, which is slightly different from Haberman and Ratcliffe, who found that banks have a positive effect on crime at all hours [50]. There are many bars in the old district, and the bars are open from nighttime to dawn the next day. During this period, many people will gather near the bar. After drinking, people will relax their awareness of vigilance and become potential victims of street property crimes [13, 53]. Restaurants are generally open for longer hours, and this study found a positive relationship between all periods and street property crimes. The restaurant is one of the crime attractors proposed in the RAT. Related studies found a significant positive effect of restaurants on street crimes before dawn [54] and at nighttime [55]. The results of this research on openness are different from the existing research. Among the streetscape variables in this study, the number of crimes was positively correlated with openness. But some studies have shown that increasing the proportion of sky in the street can promote the openness of public space, thus reducing crime [38]. There is only one explanation for the negative correlation between the two variables: the distance to the nearest police patrol station and grocery store. Security posts, police stations, and police offices as formal control institutions are crime inhibitors. However, distance to the nearest police station has a negative effect on crime occurrence, i.e., proximity to a police station increases crime rates, which is consistent with the findings of numerous previous studies [43, 56, 57].

This study found that proximity to police patrol stations increases crime rates. Police patrol stations are usually located in busy areas with high population density and high mobility. Potential offenders are more likely to prefer places with more opportunities to commit crimes and are less likely to be influenced by police presence in their choice of crime location than to be afraid of police supervision of crimes. Victims are more likely to promptly notify police if they are assaulted near a police presence [56].

There are six variables: road coverage, greenness, proximity, convenience stores, bubble tea and cafes, and police cameras, which showed positive and negative explanations for crime cases in all time periods. This study found that the relationship between roads and crime changes over time. It will inhibit crime during the daytime and promote crime at nighttime and before dawn. In previous studies, the relationship between roads and crime has been controversial. Different scholars believe that roads can inhibit crime [41], promote crime [22, 38], and do not have a significant relationship with crime [7]. Road coverage in the old district was positively correlated with the number of crimes before dawn and nighttime. The roads are wide and less pedestrianized at this time, and they lack effective natural surveillance. There was a negative correlation during the daytime when wide streets had higher pedestrian traffic and adequate natural surveillance. There is a high correlation between green spaces and crime, but current research on the relationship is inconclusive and the findings vary widely [7, 38, 40]. This study found that greenness during the daytime in the old district is positively correlated with crime, and greenness at nighttime and before dawn is negatively correlated with crime. Convenience stores are usually located in places with high traffic density. A large number of customers in convenience stores during the daytime increase the chance of crime [8]. The convenience stores before dawn are one of the few business spots in the city, and the bright lights through the glass windows increase natural surveillance. Of all periods, only the police cameras during the daytime acted as a deterrent to crime, possibly because potential offenders recognized the cameras during the daytime when there was good visibility, creating effective formal surveillance. Other times of the day are dimly lit, making it difficult to identify crimes through video surveillance and decreasing the deterrent effect on potential offenders [18].

5.2. Recommendations to Reduce Crime in the Old District. In urban construction, planners can optimize the spatial layout and socioeconomic elements of the environment in urban construction and development to play a key role in preventing the old district street crime. By studying the relationship between the geographic environment and street crime, scientific policy recommendations can be provided to urban planning and construction departments to design or renovate the old district streetscape environment from the perspective of crime prevention. The study recommends installing fencing in public places and clearing bike lanes and sidewalks to maintain visibility, thus preventing crime through natural surveillance and preventing offenders from escaping, it is best to avoid building wide sidewalks for old residential areas, which can reduce residents' sense of safety [38]. Sampson et al. argue that sidewalks facilitate pedestrian and social interaction activities and that neighborhood interaction enhances the sense of territory and belonging of residents, making them more willing to detect and stop potential or ongoing crimes [58]. Idle plots in the old district will have a negative impact on residents' sense of security, and the planning and construction of idle plots should be accelerated. Idle land that has been in the development stage for a long time has become a security blind spot because no one is using it, especially at night. It lacks effective natural surveillance and mechanical surveillance and has become an unsafe space where people fear crime.

The built environment plays an important role in inducing or preventing crime. In violent crime, decaying built environments such as abandoned buildings, graffiti, dense litter, poor lawn conditions, dilapidated exteriors, and broken windows are positively associated with violent crime, which makes neighborhoods with high proportions of vacant and rental dwellings require more police resources [42]. In drug crimes, buildings can interfere with natural surveillance, and the built environment provides hiding places for drug-related offenders [22]. CPTED suggests that fences and walls promote a sense of territoriality to limit crime [4, 59]. However, the literature suggests that there is spatial heterogeneity in the effects of fences and walls on crime. Fences were negatively associated with crime on better-off streets, but the opposite was true on less-economic streets. Fences can limit crime through a sense of territoriality and provide hiding space for offenders, while fences do not block the view from either side, so they are negatively associated with crime [37]. The rectification of urban order is conducive to creating a safe environment. The commercial facilities on both sides of the roads in the old urban area need to be replanned and strictly managed. Improving the level of environmental governance reduces the opportunities for potential criminals to have close contact with criminal targets.

Among natural surveillance measures, the density of streetlights may show a positive correlation with property crime, and related studies have found that more lighting is associated with streets becoming crime hotspots and that better street lighting is located on busy streets with more pedestrians and traffic volumes [60], which can be useful for police departments in developing nighttime street patrol measures. Municipalities need to regularly overhaul streetlights to ensure that streetlights in the old district can be used effectively. In general, objective or perceived green spaces are associated with fear of crime. Research shows that more urban green space is associated with a higher perception of community safety. People use streets with more greenery more frequently, thus increasing natural surveillance. In addition, many forms of vegetation on the streets maintain visibility and do not promote fear of crime in the neighborhood. This implies that street vegetation may suppress fear in cities. Therefore, it seems appropriate to increase street greenery in crowded urban areas to create communities with a higher sense of safety [39].

Findings on patterns and factors influencing street property crime in the old district can provide a scientific basis for police to combat crime accurately. Analyzing multiscale relationships between crime and various environmental characteristics can help deploy police resources to prevent crime more effectively. Understanding key crime attractors and their ranges can provide police with guidance on the geographic location and extent of key patrols, making interventions more effective [37]. Relevant departments can formulate police patrols and plans based on the characteristics of the old district street property crimes and select more targeted areas for fixed-point police patrols at different periods. Formulating police patrol strategy configurations based on the characteristics of crimes at different periods of time can not only improve the pertinence of crime prevention and control but also save limited police forces and improve the efficiency of security patrols. It is also necessary to conduct a thorough inventory of existing police cameras to cover as many dead corners in the streets as possible and add warning light signals next to police cameras to deter potential criminals at night. Research conclusions can also provide empirical data for publicizing crime prevention. Introducing the necessary knowledge of crime prevention into daily life to the old district residents can improve their awareness of public security and safety prevention, reduce the urban crime rate, and create a crime-free city.

6. Conclusions

Based on environmental criminological theories such as CPTED, RAT, and CPT, this study explores the characteristics of criminal activities by using the old district street property crimes as the research object. After extracting physical environmental characteristics from street view images using the FCN visual image semantic segmentation algorithm with POI data as the built environment characteristics of the study area, we used a negative binomial regression model to analyze the factors influencing multitemporal street property crimes, and the study found that:

(1) There are temporal and spatial differences in cases of street property crime. In terms of time, the number of crime cases shows "three peaks and two troughs" characteristics, in which the number of cases before dawn is the highest, 2:00 is the highest period, and the number of cases fluctuates with time during the daytime. 10:00 is the least nighttime crime case on a sound stage. There was a significant difference in the number of crimes on both work days and rest days, with the highest number of crimes on Wednesday and the lowest on Thursday. In terms of space, crime cases show the characteristics of spatial agglomeration, mainly concentrated in the bustling commercial areas, where the city's main roads are located. The number of crimes in residential areas is relatively low.

(2) Street view variables, formal social control variables, and built-environment variables had a significant effect on the occurrence of street property crime. During the whole day, openness, banks, bars, and restaurants had a significant positive effect on crime occurrence; closeness, police cameras, grocery store, and distance to the nearest police patrol station had a significant negative effect on crime occurrence.

(3) There are two explanations for the positive and negative correlations between some environmental variables and street property crimes before dawn, during the daytime, and at nighttime. Road coverage before dawn, greenness, closeness, and convenience stores in the daytime, and road coverage, closeness, bubble tea and cafe, and police cameras in the nighttime have significant positive effects on crime occurrence; closeness, greenness, convenience stores before dawn, road coverage, police cameras, bubble tea and cafe in the daytime, and greenness in the nighttime have a significant negative impact on crime occurrence.

The research in this paper is also deficient, limited by the data, and does not consider the impact of the light environment before dawn and at nighttime on crime. Technical limitations of BSV prevent access to updated real-time street view data, which may not accurately reflect changes in the street environment. At the same time, street view collection vehicles cannot access some side streets or alleys in the old district where only pedestrians pass and cannot ensure the integrity of street view images in every street segment and every urban space. In the future, the relationship between ambient brightness at nighttime and crime occurrence can be explored, and the population heat map can be used as an independent variable to explore the impact of pedestrian flow on crime production. Meanwhile, the impact of the COVID-19 pandemic on the occurrence of criminal behavior should also be investigated in future research. These questions still require more in-depth research in the future.

Data Availability

The data presented in this study are available on request from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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