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Revealing the differences in bicycle theft and motorcycle theft: spatial patterns and contributing factors

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There exists abundant literature on vehicle theft, but only a few studies focused on bicycle theft and motorcycle theft. This study aims to reveal and explain differences in spatial distributions of bicycle theft and motorcycle theft in ZG city, China. The key findings are as follows: (1) There are spatial disparities in the hotspots of bicycle theft and motorcycle theft. Bicycle theft hotspots predominantly cluster in the urban core of ZG city, while motorcycle theft hotspots are primarily concentrated in the suburban regions. (2) At the community level, car parks, Internet cafes, and subway stations have a significant positive impact on bicycle theft, while bus stops and shops have a significant positive impact on motorcycle theft. The residential area has significant positive impacts on both bicycle and motorcycle thefts. (3) The proportion of the low-educated has a significant deterrent effect on bicycle theft but a positive impact on motorcycle theft, while the proportion of low-income residents significantly increases motorcycle theft. The proportion of migrant population and residential land area within communities have a significant positive impact on both bicycle theft and motorcycle theft. (4) Surveillance cameras have a significant positive impact on motorcycle theft, but ambient population density has a significant deterring effect on motorcycle thefts. Neither of these two guardianship variables have significant impacts on bicycle thefts. The main theoretical contribution of this study is that it provided a comprehensive assessment on the contrasting spatial distributions between bicycle thefts and motorcycle thefts and on the contrasting contributing factors for the two thefts. These findings provide a scientific basis for effective crime prevention and urban governance. A uniform strategy would not be able to prevent and reduce both bicycle thefts and motorcycle thefts. Effective strategy should target the high concentration areas and intervene the specific contributing factors for each of the two thefts.

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Introduction

Due to the exponential growth in urban travel demand, bicycles (including traditional bicycles and electric bicycles) and motorcycles (mostly gasoline powered with two wheels) have become indispensable components of China's urban transportation system(Cherry and Cervero 2007; Zhang et al. 2013). Studies have reported that China has the largest number of electric bicycles in the world, with 110 million electric bicycles in 2010, and that number grew to over 300 million by 2019 (Shao et al. 2022; Wang et al. 2023). The average number of motorcycles per 100 households in China was 34.2 by the end of 2019 (China National Bureau of Statistics 2023). With the increasing popularity and widespread use of these two modes of transportation, extensive research has been conducted. Some have compared the severity of injuries caused by bicycle and motorcycle accidents (Kent et al. 2021; Lima Júnior et al. 2012; Qian and Shi 2023), as well as the factors influencing residents' different modes of transportation(Hu et al. 2018; Hu et al. 2022).

Thefts involving electric bicycles have been rising, and motorcycle theft contributed to a significant portion of motor vehicle thefts in China (Mao et al. 2018; Zhang et al. 2007; Zhang, 2016). Taking Beilun District, Ningbo, China as an example, Zhang (2016) showed electric bicycle thefts accounted for over a quarter of all thefts during the period from 2013 to 2015. The number of these incidents gained 1305, or a 58.05% increase from 2013 to 2015. There were 7,983 motor vehicle thefts and 6,260 non-motor vehicle thefts recorded between 2002 and 2007 in Shanghai, China (Mao et al. 2018). Most stolen motor vehicles were two-wheeled gasoline motorcycles, with only a few being cars or light trucks, while non-motor vehicles were predominantly bicycles and electric bicycles (Mao et al. 2018). Furthermore, a study revealed that 67.2% of respondents had encountered bicycle thefts in the previous five years in Tianjin, China (Zhang et al. 2007).

A few studies have revealed spatially uneven distribution patterns of motorized vehicle theft (Fuentes and Jurado 2019; Hodgkinson et al. 2016; Lu 2006; Mao et al. 2018; Piza et al. 2016; Vilalta and Fondevila 2019), with a concentration in or near parking stations, shopping centers, and entertainment venues; at the centers of suburban districts with many floating or non-local people. Another study has found that non-motorized vehicle theft commonly took place close to facilities where bicycles are frequently parked or in residential areas with insufficient property management(Mao et al. 2018). There have been no studies that explicitly focused on the spatial distribution of bicycle and motorcycle thefts in Chinese cities.

In addition to spatial distribution of vehicle thefts and their associated places, their contributing factors have also been explicitly tested using regression models in the literature. The selection of explanatory variables is mainly based on routine activity theory, crime pattern theory, or social disorganization theory. Routine activity theory (Cohen and Felson 1979) posits that crime is the result of the convergence of motivated offenders, suitable targets, and the absence of guardianship in time and space. Crime pattern theory(Brantingham and Brantingham 1995) provides a more detailed description of activity spaces and categorizes places and facilities with concentrated criminal activities as crime generators and crime attractors. Social disorganization theory emphasizes the role of social environment in neighborhoods on crime (Shaw and McKay 1942). This theory posits that communities with characteristics such as poverty, population heterogeneity, and residential turnover often exhibit higher crime rates due to their limited capacity to exert informal social control effectively. Badiora (2017) found that the rate of auto thefts were determined by opportunity, the flow of cars such as those in parking lots, the level of guardianship and social disorganization factors such as unemployment in Lagos, Nigeria. Rice and Csmith (2002) observed that routine activity variables such as parking lots, hotels, commercial places, and restaurants, as well as social disorganization variables, including the number of single-parent families and the number of African Americans, had a significant positive association with higher rates of auto theft in a southeastern United States city. Piza et al. (2016) found that risk factors such as disorder calls for service, multi-family housing complexes, parks and commercial zoning were significantly associated with motor vehicle theft in Colorado Springs, while population density had a negative relationship with car theft. Fuentes and Jurado (2019) found that certain opportunity measures, such as the presence of commerce and service areas and the percentage of vehicle availability per household, are positively related to motor vehicle theft in Ciudad Juárez, Mexico, while capable guardianship measures such as population density are negatively related. Social control factors, such as the percentage population born in another state and percentage of people without social security coverage, also have a negative impact on motor vehicle theft. Roberts and Block (2012) found that unemployment and auto-related businesses were positively associated with permanent motor vehicle theft in North Carolina, while the percentage of households with high disposable income had a negative effect. Suresh and Tewksbury (2013) observed heavy concentration of motor vehicle thefts in the neighborhoods characterized by indicators of social disorganization such as poverty, unemployment, and vacant houses in Louisville, USA. Walsh and Taylor (2007) analyzed motor vehicle theft in a Midwestern US city from a social disorganization perspective. They found that motor vehicle thefts were most common in neighborhoods with low socio-economic status and that these neighborhoods were surrounded by other neighborhoods with high motor vehicle theft rates. However, existing studies often failed to simultaneously integrate routine activity theory, crime pattern theory and social disorganization theory, they tended to focus on only one or two of these theories (Badiora 2017; Rice and Csmith 2002; Roberts and Block 2012; Suresh and Tewksbury 2013; Walsh and Taylor 2007). Their measure of guardianship was limited to census population (Fuentes and Jurado 2019; Piza et al. 2016), which cannot capture mobility or routine activities of the population. While Andresen (2005) used ambient population density to explain automobile theft. His ambient population was obtained from the LandScan Global Population Database nearly 20 years, which was model-based estimation, not as accurate as the more recent ones from mobile phone data.

Only a few studies specifically targeted bicycle thefts. Chen et al. (2018) analyzed incidents of bicycle theft at intersections and mid-blocks in Seattle, revealing that the presence of certain public amenities, such as sidewalks, bicycle lanes, bus stops, and bike racks, as well as communities with a higher proportion of socially disadvantaged individuals and a lower median age, are more susceptible to bicycle theft in Seattle, Washington. Levy et al. (2018) found that bike thefts around Metro stations in Washington DC are positively influenced by the number of bikes parked and the volume of auto-related larcenies, but negatively associated with the number of nearby businesses. Mburu and Helbich (2016), using street segments as their analytical unit to aggregate the frequency of bicycle thefts, discovered that facilities such as train stations, vacant houses, pawnshops, bicycle stands and ethnic heterogeneity positively increased bicycle thefts in London, UK. Only one such study is found in China. Zhang et al. (2007) showed that the house type of row houses and number of adult household members are significant protective factors, whereas neighborhood poverty level and neighborhood deviance and/or crime level are risk factors for bicycle theft in Tianjin, China. This study is based on survey data, not official crime data from police department. The representativeness of the survey sample may impact the results. There have been no studies that explicitly focused on bicycle thefts using official crime data in China.

Only one study compared thefts between motor vehicles and non-motor vehicles. Mao et al. (2018) uncovered that both the permanent population and density of floating population significantly contributed to thefts of both types of vehicles. Intersection density and the number of commercial places have different effects on these two types of vehicles. While motor vehicles included motorcycles and non-motor vehicles included bicycles, the study did not explicitly examine motorcycles and bicycles. Further, the factors considered in the regression models were far fewer than what have been reported in the literature.

In sum, motorcycle and bicycle thefts are severe problems in China. Virtually all previous studies did not extract bicycle thefts from non-motorized vehicle thefts, except for a few based on survey. Likewise, they did not extract motorcycle thefts from motorized vehicle thefts. The guardianship measure was based on residential population or model estimated ambient population, which are not accurate representations of the real ambient population. The explanatory variables were often limited to one or two theories. There have been no studies that explicitly focused on the spatial distribution and statistical modeling of bicycle and motorcycle thefts using official crime data in Chinese cities. Given these gaps in the literature, this study investigates the spatial distribution patterns in bicycle and motorcycle thefts in ZG city, China, using the combination of routine activity theory, crime pattern theory and social disorganization theory. Cell phone based ambient population will be used to measure guardianship.

Data and method

Study area. ZG city is a major metropolitan in the Guangdong-Hong Kong-Macao Greater Bay Area. It serves as an international business center and a comprehensive transportation hub that accommodates a diverse foreign population and a complex transportation system with various modes of transport. Bicycles and motorcycles are essential means of transportation for many people. The city encompasses 11 districts. The 2 districts predominantly covered by forests and agricultural lands (Long et al. 2020) are removed from the study. The remaining 9 districts with 2151 communities serve as the research area (Fig. 1).

Data source and variables

Dependent variables. Traditional bicycles are non-motorized two-wheel vehicles, while electric bicycles and motorcycles are

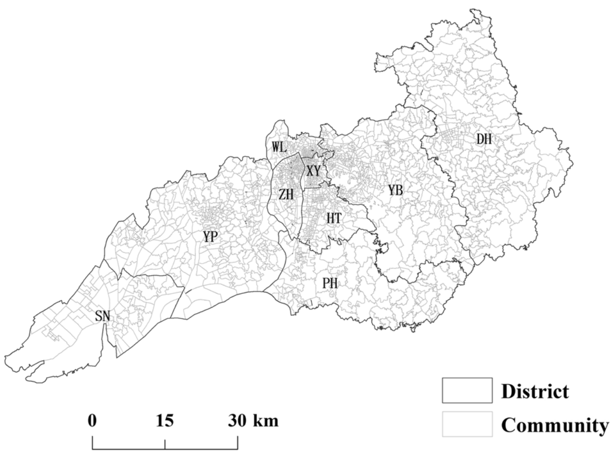

Fig. 1 Map of the research area.

motorized two-wheel vehicles. Literature suggests that people tend to use traditional bicycles and electric bicycles for short-distance travel (Hu et al. 2018) but are more inclined to choose motorized transportation for long-distance travel (Pan et al. 2009). Therefore, this study groups traditional bicycles and electric bicycles into the same broader category called "Bicycle." The term "Bicycle" refers to both the traditional bicycles and electric bicycles in the remainder of the paper.

Crime data were obtained from the ZG Police Department, comprising thefts of both (traditional and electric) bicycles, as well as motorcycles in 2019. The thefts are restricted to the stealing of the whole vehicle. Thefts of batteries or other parts of a vehicle are not included in this study. Bicycle and motorcycle thefts were aggregated to individual communities. The number of bicycle thefts and the number of motorcycle thefts in a community serve as the dependent variables for analysis.

Independent variables. The independent variables were based on the literature and relevant theories. The selection of crime attractors and generators followed the crime pattern theory, concentrated disadvantage variables followed the social disorganization theory, and guardianship variables followed the routine activity theory. The following paragraphs illustrate the support of the selections from the literature and theories.

Crime attractors and generators: Based on the literature review and the crime pattern theory, this study selected the number of car parks, bus stops, subway stations, internet cafes, and shops to represent crime attractors and crime generators. These points-of-interest (POIs) are extracted from a 2020 Daodaotong electronic map. In addition, we also measured residential land area for each community from a land use map. The residential land area and all POIs are common places for bicycles and motorcycles to park. The following are justifications of the selections.

Car parks, common locations for vehicle parking, provide continuous potential targets for motivated offenders, making them high-risk areas for vehicle theft. Badiora (2017) found that the highest ratio of vehicle theft occurred in car parks and garages in Lagos, Nigeria. Suresh and Tewksbury (2013) observed that an elevated rate of motor vehicle theft occurs where the number of car parks is higher in communities surrounding churches in Louisville, USA.

Subway stations and bus stops attract substantial pedestrian traffic, thus acting as crime attractors. Levy et al. (2018) observed a higher incidence of bicycle theft near subway stations in Washington, USA, attributing it to the dense concentration of bicycles parked around these stations. Chen et al. (2018) also found that the presence of bus stops is positively associated with bicycle theft in Seattle, Washington. In contrast, Li and Kim (2022) found in New York City, USA, that with each additional subway station, the risk of auto theft decreases by approximately 5%, a phenomenon linked to the lower number of cars around subway stations and increased natural surveillance.

Shops, including convenient stores, being frequented by customers, draw the attention of potential offenders. Fleming (1999) discovered that some adolescents exploited the high mobility of individuals as cover and make shops as "hunting grounds" for car theft. Similarly, Hollinger and Dabney (1999) and Lu (2006) identified shopping centers as high-risk locations for motor vehicle theft.

Internet cafes often located in commercial areas or near transportation hubs serve as popular entertainment venues for socially disadvantaged young adults(Dongping Long and Liu 2022; Song et al. 2017). Studies have revealed a positive correlation between car theft and the number of young male individuals in a population (Badiora 2017; Piza et al. 2016;

Roberts and Block 2012). While no publication has explicitly established a link between Internet cafes and vehicle theft, such linkage is possible because of the concentration of young adults.

Residential areas are concentrated with populations and parking lots/garages, potentially leading to the convergence between potential criminals and targets. Mao, et al. (2018) found a significant concentration of motor vehicle theft and non-motor vehicle theft in residential areas in the eastern part of Shanghai, China. Similarly, Lu (2006) discovered that car thefts are more likely to occur in densely populated residential areas in Buffalo, New York.

Concentrated disadvantage variables: Based on the literature review and social disorganization theory, this study selected domestic migrants, education attainment, and income to represent concentrated disadvantages. The proportions of the domestic migrant population and low educated individuals are retrieved from the seventh national census data. The proportion of migrant population is defined as the ratio of non-local residents to the total community residents. Similarly, the proportion of the low-educated is calculated by dividing the number of individuals with an education level below high school by the total community population. In addition, this study also quantifies the income level of the community by using the proportion of low-income residents from China Unicom's DAAS platform. Unlike single-indicator-based economic status indicators, China Unicom uses a combination of indicators based on users' residential and behavioral characteristics, such as housing prices, mobile device prices, modes of transportation (airplane, high-speed train, train, etc.), and travel volume to other cities. These indicators are integrated through machine learning to compute an index for representing a more comprehensive and reliable measure of users' socio-economic background. This data, based on 500 m*500 m grids, is aggregated to census communities using proportional area assignment. The proportion of low-income residents refers to the percentage of people whose annual income is typically below 50,000 yuan. This measure of low-income is more comprehensive than the low-income data from the Census. The following are further justifications of the selections.

The proportion of migrant population represents residential instability, which is characterized by residents frequently moving in and out of a community. Most migrants live in rental properties with a high turnover rate. Residential instability is found to correlate with heightened crime rates (Miethe et al. 2001; Walsh and Taylor 2007). Miethe et al. (2001) and Walsh and Taylor (2007) have found an increase in motor vehicle theft cases strongly associated with residential instability.

The proportion of the low-educated represents educational attainment. Sanchez Salinas and Fuentes Flores (2016) found that high educational level significantly promotes the occurrence of vehicle theft. This seems to contradict the normal pattern of crime concentration in low education attainment areas. However, prevalence of vehicle in more affluent areas with high education attainment may explain these findings.

The proportion of low-income residents represents income level. Roberts and Block (2012) discovered a negative correlation between household income and motor vehicle theft in North Carolina, attributing to the ownership of vehicles with advanced security systems that increase guardianship levels. Suresh and Tewksbury (2013) found that as the median income increased, the number of motor vehicle thefts decreased in Louisville, USA. Similarly, Zhang et al. (2007) revealed a negative association between bicycle theft and household income but a positive correlation with neighborhood poverty levels in Tianjin, China.

Guardianship variables: Based on the literature review and routine activity theory, this study selected surveillance cameras and ambient population densities to represent guardianship that might deter bicycle and motorcycle thefts. Liu et al. (2020) found that surveillance cameras had a significant reduction effect on theft-related crimes in Gusu District in Suzhou, China. Long et al. (2021) discovered surveillance cameras played a guardianship role and had significant negative impacts on street robbers' crime location choice in ZG city China.

Ambient population is measured by the average daily mobility from ZG City's mobile phone signaling data collected in October 2019. This data source consists of desensitized and aggregated mobile phone data obtained from China Unicom, a major mobile communication operator in China. Mobile data or call detail records capture the location of a phone each time a call, text message, or data request is initiated (Song, et al. 2023). A mobile phone user who stayed within a 500 m*500 m grid for more than half an hour is counted toward the ambient population of the grid. We summarized the ambient population for the entire month, divided the monthly total by 31 to give an average daily count, and further divided the average daily count by area of each community to create the ambient population density.

Traditional research often uses residential population data or census data to link crime in an area to the number of residents, in order to estimate potential risk population (Fuentes and Jurado 2019; Piza et al. 2016). However traditional population data has limitations as it doesn't account for population mobility and is static (Yue et al. 2024). In recent years, criminology research has increasingly applied large-scale location data, such as mobile phone data and geotagged social media, to measure the ambient population, providing a viable alternative to traditional census and survey data (Hanaoka 2018; Song et al. 2023; Song et al. 2018; Tucker et al. 2021). Research has shown that the ambient population can deter crime, acting as a form of guardianship (Boivin 2018; Long et al. 2021). For example, Boivin (2018) suggested that the relationship between burglary location choices and ambient populations was negative. Similarly, Long et al. (2021) found that the ambient population plays a guardianship role and has a negative and deterrent effect on the crime location choices of street robbers.

Restricted motorcycle area: The city government prohibits motorcycles in the inner city. To account for the impact of this factor, this study used a dummy variable distinguish restricted areas from non-restricted areas.

A total of 12 independent variables were used in the modeling process. Table 1 displays the descriptive statistics for both the independent and dependent variables.

Table 2 shows the correlation coefficients variance inflation factor (VIF) among the independent variables. The outcomes revealed that the maximum VIF value is 2.46. Furthermore, the absolute values of the correlation coefficients between the variables are mostly less than 0.6. Therefore, the selected variables do not exhibit multicollinearity or high correlation and can be used for subsequent model fitting (Fuentes and Jurado 2019).

To facilitate the direct comparison of effects of various variables on thefts, we standardized the different measurements to z scores. The standardization formula is as follows:

$$x' = \frac{x - \mu}{\sigma} \tag{1}$$

In Eq. 1, μ is the mean of a variable, and σ is the standard deviation of the variable.

Research methods. This study initially utilizes Kernel Density methods to examine the spatial distribution characteristics of bicycle theft and motorcycle theft. Subsequently, Spatial Point Pattern Test is employed to identify statistically significant

Table 1 Descriptive statistics of dependent and independent variables.

Variables	Code	Mean	SD	Min	Max
Dependent variables:					
Bicycle theft (count)	y_1	0.760	2.117	0	38
Motorcycle theft (count)	y_2	0.972	2.740	0	29
Independent variables:					
Car parks (#)	X_1	11.760	14.732	0	274
Bus stops (#)	X_2	3.709	4.761	0	99
Subway stations (#)	X_3	0.367	1.212	0	16
Shops (#)	X_4	7.189	10.670	0	140
Internet cafes (#)	X_5	1.265	2.264	0	25
Residential land area (m^2)	X_6	188525.600	222877.480	33.969	2419671.500
Proportion of migrant population (%)	X_7	0.422	0.229	0	0.980
Proportion of the low-educated (%)	X_8	0.483	0.170	0.017	0.912
Proportion of low-income residents (%)	X_9	0.184	0.037	0.055	0.559
Surveillance cameras (#)	X_{10}	2.519	7.343	0	111
Ambient population density (#/km^2)	X_{11}	21227.550	25715.250	7.418	494560.700
Restricted motorcycle area (dummy)	X_{12}	0.417	0.493	0	1

Table 2 Correlation coefficient matrix for the independent variables.

Variables	VIF	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
X_1	2.42	1.000											
X_2	1.98	0.622	1.000										
X_3	1.17	0.319	0.287	1.000									
X_4	2.39	0.476	0.429	0.213	1.000								
X_5	1.59	0.402	0.289	0.100	0.577	1.000							
X_6	1.64	0.101	0.325	0.078	0.335	0.098	1.000						
X_7	1.38	0.103	0.207	0.039	0.429	0.262	0.137	1.000					
X_8	1.85	−0.348	−0.040	−0.156	0.048	−0.085	0.324	0.121	1.000				
X_9	1.27	−0.011	−0.128	−0.007	−0.057	−0.003	−0.209	−0.207	−0.086	1.000			
X_{10}	1.22	0.170	0.289	0.129	0.115	0.068	0.291	0.151	0.145	−0.128	1.000		
X_{11}	1.58	0.165	−0.059	0.123	0.138	0.155	−0.356	−0.016	−0.370	0.229	−0.184	1.000	
X_{12}	1.72	0.152	−0.094	0.091	−0.051	0.036	−0.410	−0.142	−0.471	0.255	−0.254	0.516	1.000

variations in the spatial arrangement of bicycle theft and motorcycle theft outside the restricted motorcycle areas. Finally, the research uses Negative Binomial Regression modeling to elucidate the distinct influences of the selected variables pertaining to the built environment and social environment on bicycle theft and motorcycle theft.

Spatial point pattern test. The Spatial Point Pattern Test (SPPT) method is utilized to quantify whether there are disparities in the spatial distributions of bicycle theft and motorcycle theft in the ZG city outside the restricted areas for motorcycle driving. The approach iteratively samples subsets from the testing dataset (i.e., a category of crime), constructs confidence intervals based on the sampled data, and computes the percentage of the base dataset (i.e., the second category of crime not sampled) falling within the confidence intervals of the sampled dataset(Andresen, 2009). SPPT evaluates the similarity between the two datasets by computing both the local similarity index and the global similarity index. The local similarity index has three values in −1, 0, and 1, which respectively represent that the count of points in a spatial unit in the base dataset is lower, similar, or higher than the count in the corresponding unit in the test dataset (Yang et al. 2021). The global similarity index is the division of the count of spatial units in which the local similarity index equals 0 over the total count of spatial units. It is essentially the ratio of the number of units where the counts of the two datasets are similar, over the total number of units. It ranges from 0 (indicating no resemblance) to 1 (indicating complete similarity). Typically, a value of global similarity index greater than 0.8 indicates high similarity in spatial patterns between the two point datasets, while a value lower than 0.8 suggests the two patterns being significantly different (Andresen 2009, 2016). In this study, the test dataset pertains to motorcycle theft, while the base dataset concerns bicycle theft.

Negative binomial model. The dependent variable in the study pertains to the number of crimes involving bicycle and motorcycle theft, which are non-negative integers. These criminal incidents are considered low-probability events and are typically modeled using either a Poisson regression model or a negative binomial regression model (Willits et al. 2011). The Poisson regression model assumes that the mean of the dependent variable is equal to its variance (Berk and MacDonald 2008). However, the dependent variable in this study exhibits overdispersion characteristics. Hence, the negative binomial regression model will be employed for better fitting. The negative binomial model is a compound Poisson distribution in which the Poisson mean follows a gamma distribution. Its probability expression is defined as follows:

$$\Pr = (\mathrm{Y} = \mathrm{y}|\mu, \alpha) = \frac{\Gamma(\alpha^{-1} + \mathrm{y})}{\Gamma(\alpha^{-1}) + \Gamma(\mathrm{y} + 1)} \left(\frac{a^{-1}}{\alpha^{-1} + \mu}\right)^{a^{-1}} \left(\frac{\mu}{\mu + a^{-1}}\right)^{y} \tag{2}$$

In Eq. 2, Y represents the dependent variable, which is the number of reported theft incidents involving bicycles and motorcycles in various communities within the ZG city research area in 2019. $\mu = \mathrm{E}(y)$ denotes the expected value function. α

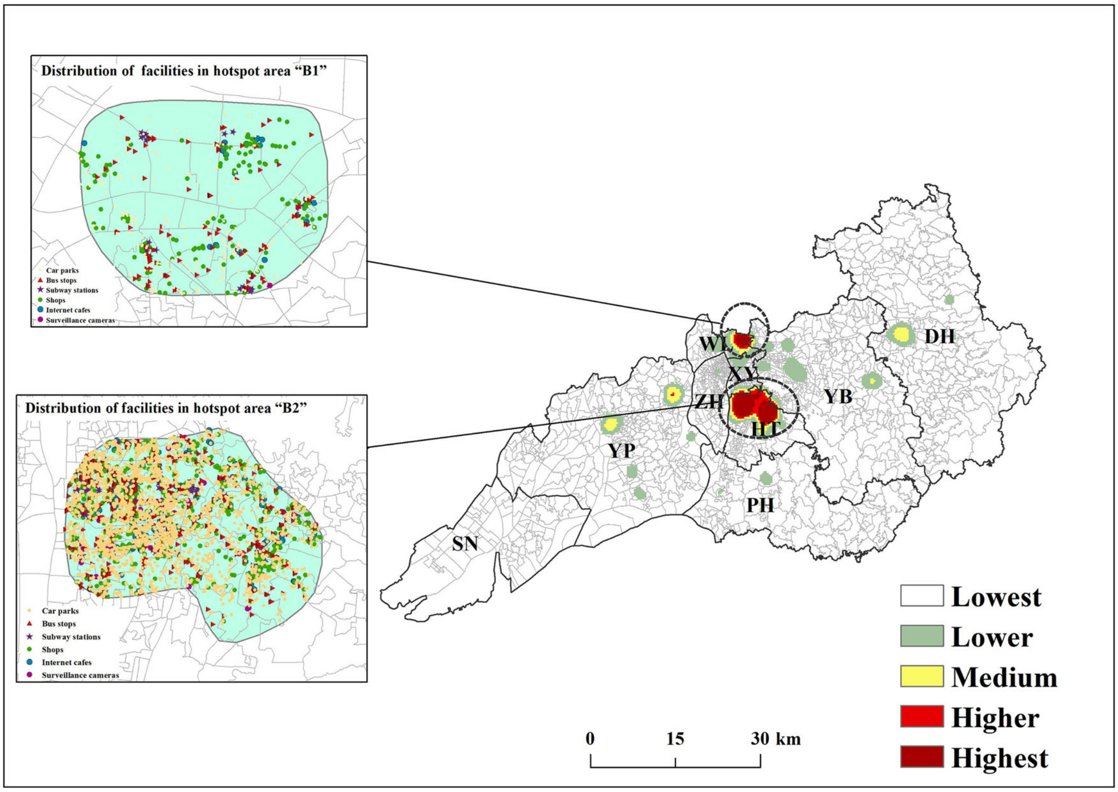

Fig. 2 The spatial distribution of bicycle thefts and POI facilities in the hotspots.

represents the variance parameter of the Gamma distribution. When α approaches 0, it indicates the absence of over-dispersion in the data, and the negative binomial model transforms into a Poisson regression model. The marginal effect of the explanatory variables in the model is referred to as the incidence rate ratio (IRR), which signifies that for every one-unit increase in the explanatory variable x, the probability of the event occurring will increase by a factor of IRR.

Results

Comparative spatial analysis of bicycle and motorcycle thefts. The spatial distribution patterns of bicycle theft and motorcycle theft are illustrated in Figs. 2 and 3. The kernel density values of bicycle theft have been standardized using the kernel density values of motorcycle theft as a benchmark. Figure 2 clearly shows two hotspots of bicycle thefts. Hotspot area "B1" is primarily located in the old Central Business District (CBD) in the WL district, while hotspot area "B2" is centered at the new CBD, mostly in HT but also covering east part of XY district.

In contrast, the hotspots of motorcycle thefts are primarily scattered in the suburban regions (Fig. 3). Hotspot areas "M1" and "M2" are situated in YB district. Hotspot area "M3" is in DH district, further away from the CBD. Additionally, smaller motorcycle theft hotspots can also be found in the YP district and other regions.

Comparison of POI facilities in the hotspots again those in the entire study may help reveal important characteristics of the hot spot. Figure 4 shows the density of POI facilities, including car parks, bus stops, subway stations, shops, internet cafés and surveillance cameras. B2, located in the new CBD, has high densities for all 6 types of POIs, with an extremely high density of car parks. On the other hand, the densities of POIs in B1 are similar to those of entire study area. In hotspots of motorcycle thefts, densities of POIs are mostly higher than those in the entire study area, Surveillance camera densities are similar but slightly lower, while subway station densities are lower than in the entire study area, because there exist far less subway lines and stations in the suburbs. Based on these observations, it can be generalized that bicycle theft hotspots occur at CBDs with very high or average concentration of POIs, while motorcycle theft hotspots occur at suburb locations with high POI densities.

It may be useful to examine the makeup of POIs in the hotspots, in comparison with the entire study area (Fig. 5). In B2, the car parks dominate other POIs. In all 3 motorcycle theft hotspots, shops are the dominant POI. Whether these observations are statistically significant are to be tested with the negative binomial regression models.

Spatial point pattern analysis of bicycle theft and motorcycle theft. Visual inspection of Figs. 2 and 3 shows that the spatial distribution of bicycle thefts is different from that of motorcycle thefts. Since there is virtually no motorcycle theft in the motorcycle restricted area, comparisons between the spatial distributions of the two types of thefts were carried out outside of the restricted area. The local similarity indices of SPPT are mapped in Fig. 6. Most communities have a significantly lower number of bicycle thefts than that of motorcycle thefts (shown in yellow), while only a few communities have a significantly higher number of bicycle thefts than that of motorcycle thefts (shown in red). The global similarity index of 0.611 is below the threshold of 0.8 (Andresen 2009, 2016), indicating a lack of significant similarity between the spatial distribution patterns of bicycle thefts and motorcycle thefts. The statistically significant differences are illustrated in the local similarity index distribution map (Fig. 6).

Comparative analysis of influencing factors. Using the Stata software, a negative binomial regression model was constructed to explore the impact of crime attractors and generators, social

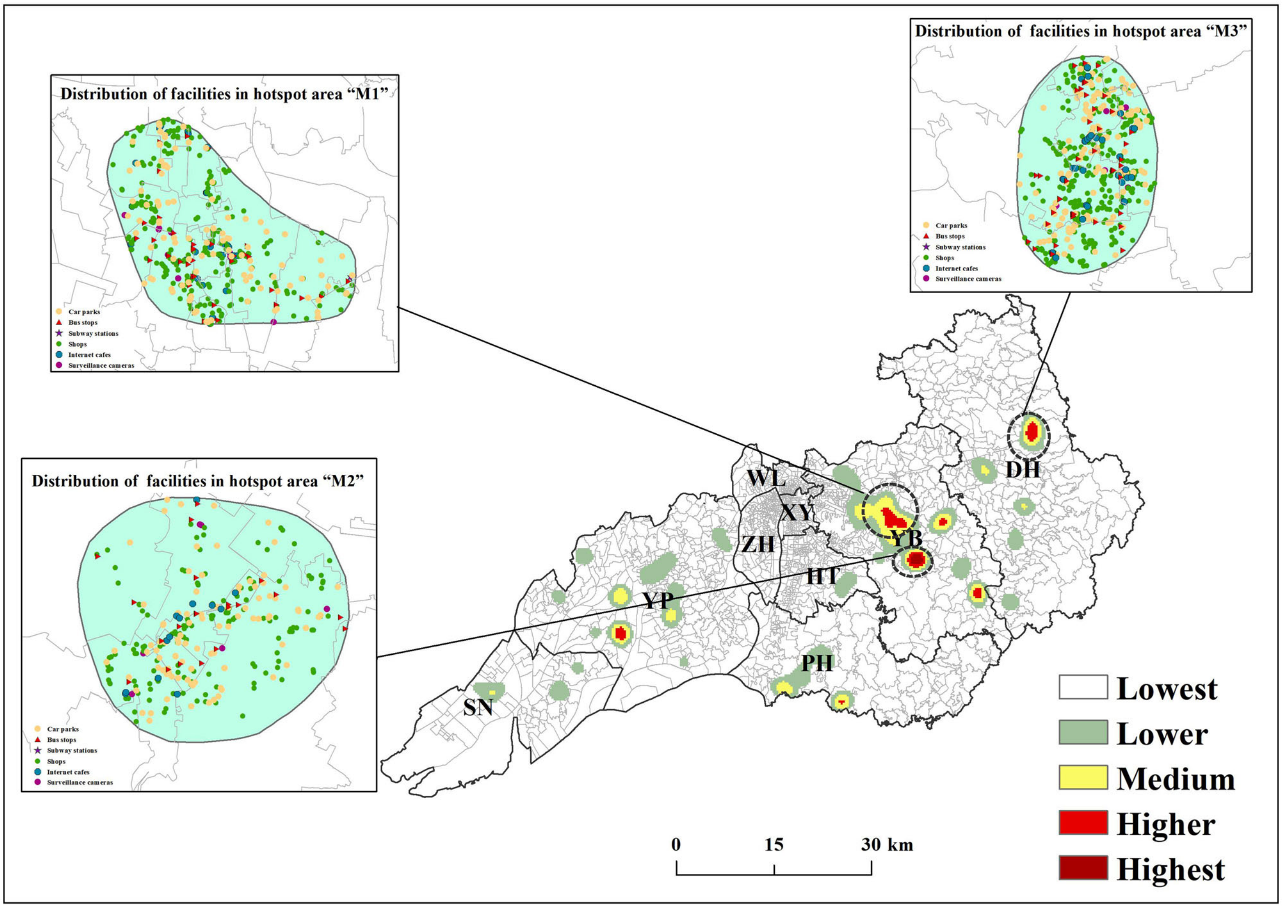

Fig. 3 The spatial distribution of motorcycle thefts and POI facilities in the hotspots.

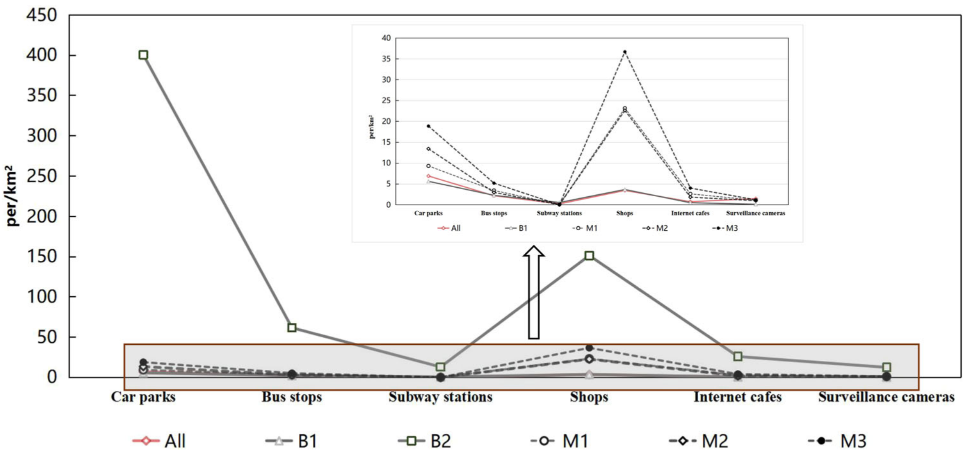

Fig. 4 Density of POI facilities in the hotspots, in comparison of the study area.

disorganization variables and ambient population on bicycle theft and motorcycle theft at the community level. In the negative binomial regression model (Table 3), the significance of the correlation was measured by p-value. The regression coefficient Beta indicates the direction (positive or negative) of the correlation between each independent variable and the dependent variable, while the Incident Rate Ratio (IRR) demonstrates the marginal effect of explanatory variables. Pseudo R-squared serves as a metric for evaluating model fit within the negative binomial regression framework. The Akaike Information Criterion (AIC) (Liu 1980) and the Bayesian Information Criterion (BIC) (Fu et al. 2015) are both criteria for goodness of fit.

Model 1 results (Table 3) reveal four statistically significant variables in car parks, subway stations, internet cafes, and residential land area, with an IRR of 1.395, 1.139, 1.238, and 1.161 respectively. Regarding community social characteristics, the proportion of migrant population has a significant positive effect on bicycle theft, with an IRR value of 1.595. Conversely, the proportion of the low-educated has a significant negative effect on bicycle theft, with an IRR value of 0.771. Neither

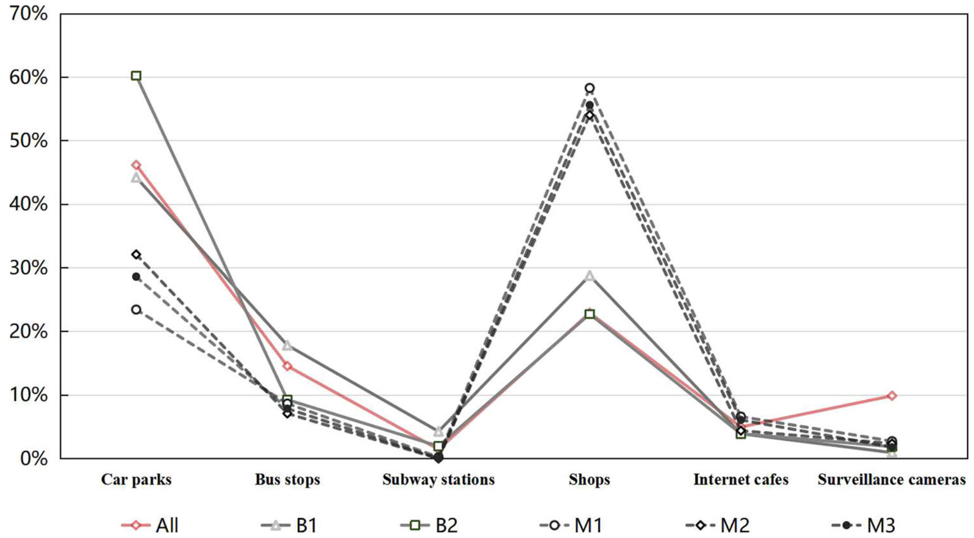

Fig. 5 The makeup of POI facilities in the hotspots, in comparison with the entire study area.

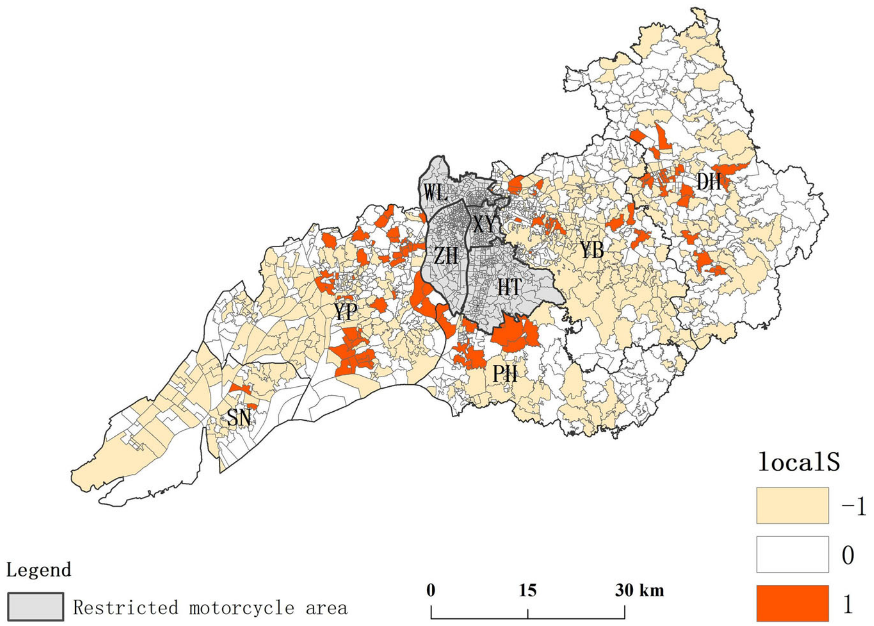

Fig. 6 Map of local similarity index in the spatial point pattern test.

surveillance cameras nor ambient population density have a significant impact.

According to Model 2 (Table 3), bus stops, shops, and residential land area have significant positive effects on motorcycle theft, with an IRR value of 1.286, 1.516, and 1.184 respectively. The proportion of migrant population and the proportion of low-income residents also have a significant positive effect on motorcycle theft, with an IRR value of 1.510 and 1.121 respectively. In terms of the guardianship variables, the surveillance cameras have a significant positive impact, with an IRR of 1.118, while ambient population density has a significant negative impact, with an IRR of 0.475. The contrasting impacts between these two variables are explained in the discussion section.

There are several notable differences between the two models. First, car parks, subway stations, and internet cafes have a significant positive influence on bicycle theft, while bus stops and shops have a significant positive influence on motorcycle theft. As shown in the hotspot analysis, motorcycle theft incidents are mainly concentrated in suburban areas. Transportation is less convenient in suburban areas, and people rely on motorcycles for long-distance travel. On the other hand, bicycle theft hotspots are mainly concentrated in the central urban area. Transportation is more convenient in the central urban areas, and people rely on electric bicycles/bicycles for short-distance travel. Second, proportion of low education attainment exerts a significant deterring effect on bicycle theft but no significant influence on motorcycle theft. Conversely, the proportion of low-income residents has a significant positive effect on motorcycle theft but no significant impact on bicycle theft. Third, surveillance cameras have significant positive effects on motorcycle thefts but no effect on bicycle thefts. Ambient population density significant deterring effects on motorcycle thefts but no effect on bicycle thefts.

However, there are also similarities between the two models. The residential land area and the proportion of domestic migrant population significantly promote the occurrence of bicycle and motorcycle theft cases. Both types of thefts seem to follow residential areas, especially villages in the city, where domestic migrants tend to concentrate (Liu et al. 2018; Xu et al. 2024).

Table 3 Negative binomial regression results of bicycle and motorcycle theft.

	Model 1 (bicycle theft)		Model 2 (motorcycle theft)	
	Beta	IRR	Beta	IRR
Car parks	0.333***	1.395	−0.082	0.921
Bus stops	0.008	1.008	0.252**	1.286
Subway stations	0.130*	1.139	0.095	1.100
Shops	0.086	1.089	0.416***	1.516
Internet cafes	0.214***	1.238	0.080	1.083
Residential land area	0.149**	1.161	0.169**	1.184
Proportion of migrant population	0.467***	1.595	0.412***	1.510
Proportion of the low-educated	−0.26***	0.771	0.061	1.062
Proportion of low-income residents	−0.005	0.995	0.114*	1.121
Surveillance cameras	0.024	1.024	0.112***	1.118
Ambient population density	−0.070	0.933	−0.744***	0.475
Restricted motorcycle area	-	-	−1.826***	0.161
AIC	4362.804		4063.456	
BIC	4436.562		4142.888	
Pseudo R^2	0.092		0.197	

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

Discussion and conclusions

Discussion. We established earlier that research on bicycle thefts and motorcycle thefts is rather limited. Bicycles are often grouped into non-motorized vehicles, and motorcycles into motorized vehicles. Our study treats bicycle thefts and motorcycle thefts explicitly. Direct comparison of our study against the literature may be challenge, Still, we will strive to summarize the consistency and inconsistency below.

Our study revealed that both bicycle thefts and motorcycle thefts are highly clustered. This is consistent with uneven distribution patterns of motorized vehicle thefts(Fuentes and Jurado 2019; Hodgkinson et al. 2016; Lu 2006; Mao et al. 2018; Piza et al. 2016; Vilalta and Fondevila 2019) and clustering of non-motorized vehicle thefts (Mao et al. 2018). While previous studies often focused on either motorized vehicle thefts or non-motorized vehicle thefts, we compared the spatial distributions of bicycle theft and motorcycle theft outside of the restricted motorcycle area, confirming that the two distributions are significantly different. The hotspots of bicycle thefts are mostly in CBD, and the hotspots of motorcycle thefts are scattered in the suburbs.

The models for bicycle thefts and motorcycle thefts are quite different. This is consistent with the findings of Mao et al. (2018). Their model for non-motorized vehicle (including bicycle) thefts was very different from that of motorized vehicle (including motorcycle) thefts. The value of bicycles is typically much lower than that of motorcycles. The spatial distributions of bicycles and motorcycles are quite different, so are their thefts. It should be pointed out that the study of Mao et al. (2018) did not consider many important variables, such as different types of POIs facilities, proportion of migrant population, proportion of the low-educated and proportion of low-income residents. Our study helped fill such gap.

Our findings demonstrated that bicycle thefts are positively associated with car parks, subway stations, Internet cafes and proportion of migrant population, but negatively associated with proportion of the low-educated. Since proportion of migrant population is negatively correlated with income, our findings are consistent with a negative association between bicycle thefts and household income by Zhang et al. (2007) a positive association between bicycle thefts and socially disadvantaged people by Chen et al. (2018), and a positive association between bicycle thefts and train stations by Mburu and Helbich (2016). The positive associations of car parks and Internet cafes with bicycle thefts revealed in this study are new additions to the literature.

This study revealed that motorcycle thefts are positively associated with bus stop, shops, proportion of domestic migrants and proportion of low-income residents. It should be noted that the proportion of domestic migrants is indicative of residential instability in Chinese cities. Our findings are consistent with the positive association between motor vehicle thefts and residential instability by Miethe et al. (2001) and Walsh and Taylor (2007), the negative association between motor vehicle thefts and low income people by Roberts and Block (2012) and Suresh and Tewksbury (2013), and the positive association between motor vehicle thefts and shopping centers by Hollinger and Dabney (1999) and Lu (2006). However, our findings are inconsistent with the positive association between motor vehicle thefts and the level of education by Sanchez Salinas and Fuentes Flores (2016). In our study, this relationship is not statistically significant, albeit it is also positive.

The positive association of residential areas with both bicycle thefts and motorcycle thefts is consistent with a positive correlation between car thefts and densely populated residential areas by Lu (2006), and a significant concentration of motor vehicle theft and non-motor vehicle thefts in residential areas by Mao et al. (2018).

The findings on the guardianship variables are not completely consistent with the literature. Surveillance cameras have no significant effects on bicycle thefts but significant positive effects on motorcycle thefts. These findings seem to be counter-intuitive, as surveillance cameras are generally believed to have a deterring effect on crime. Liu et al. (2020) found that installation of surveillance cameras had a significant reduction effect on theft-related crimes in Gusu District in Suzhou, China. They also pointed out that the deterring effects decayed in time. Long et al. (2021) discovered that surveillance cameras had significant negative impacts on street robbers' crime location choice in ZG city China. They also pointed out that the magnitude of impact was relatively small, in comparison to other factors. Two factors may help explain the somewhat unexpected findings in our study. First, the surveillance cameras in ZG have been in operation for many years, therefore their impact may have diminished over the years for deterring thefts. Second, areas where facilities (POIs) are concentrated in ZG have high prevalence of surveillance cameras, as evidenced by the positive correlations in Table 2. These facilities attract motorcycles, which in turn lead to motorcycle thefts. While these explanations were supported in our field observation, they should be tested vigorously in future studies. However, it is not completely out of norm that formal or informal guardianship fail to deter crime. For example, Xu et al. (2022) showed that the presence of police facilities such as police stations do not have a significant effect on theft in ZG. A possible explanation is that police facilities may be positioned in high crime locations.

Ambient population density is the other guardianship variable in our study. It has no significant effects on bicycle thefts but significant deterring effects on motorcycle thefts. Motorcycle thefts tend to take longer time and are more difficult to execute than bicycle thefts, therefore motorcycle thefts are more prone to draw attention from the ambient population. This explains that the deterring effects of the ambient population density are more evident for motorcycles. This deterring is consistent with the findings of Piza et al. (2016) and Fuentes and Jurado (2019), who observed a suppressive effect of population density on car theft. It is also similar to the research by Long et al. (2021) and Boivin (2018), which found that the ambient population functions as a guardian in crime site selection, deterring street robbery and burglary. It is also in line with the findings of Andresen (2005) that the Landscan-based ambient population density plays a deterring role for automobile theft. Further studies should compare the effectiveness of these different measures of populations density.

Many of the previous studies on bicycle and motorcycle thefts are based on one or two theories. Our study is built on the foundation of integrating the routine activity theory, crime pattern theory, and social disorganization theory, aiming to provide a comprehensive explanation of the bicycle and motorcycle thefts. The selection of the explanatory variables (Section 2.2) is based in the integrated theories. Many of these variables are shown to have significant impacts on thefts in the models. Therefore, we conclude that the combination of these theories can effectively explain the thefts. Most of our findings are consistent with the literature, but a few are not. The explanations on the inconsistent findings are valuable additions to the literature and may inspire future research.

Nevertheless, this study is not without limitations. First, due to constraints in data availability, factors such as the ownership of bicycles and motorcycles, and security level in each community were not incorporated as control variables into the model. Consideration of additional control variable will help refine the model results. Second, bicycle and motorcycle thefts should be closely related to the spatial and temporal distribution of their usage. The lack of data on the usage leads to the problem of omitted variables in the models. Future research should develop proxy variables that reflect their usage. Third, the dependent variable in this study is sourced from crime data recorded by the ZG City Police Department. It is possible some bicycle owners may opt not to report incidents to authorities for various reasons. Since motorcycles are more valuable, the under-reporting of motorcycle thefts is expected to be less of a problem, compared to that of bicycle thefts. This difference in under-reporting could affect the modeling results, especially if the spatial distribution of such difference is not random. Nonetheless, there is no evidence of systematic bias, and the substantial theft cases and vigorous tests add confidence to our findings.

Conclusions. Based on the integration of routine activity theory, crime pattern theory, and social disorganization theory, this study developed a theoretical framework to elucidate the contrasting spatial distribution patterns of bicycle and motorcycle thefts. The main conclusions are as follows: (1) There are spatial disparities in the hotspots of bicycle theft and motorcycle theft. Bicycle theft hotspots predominantly cluster in the urban core of ZG city, while motorcycle theft hotspots are primarily concentrated in the suburban regions. (2) At the community level, car parks, Internet cafes, and subway stations have a significant positive impact on bicycle theft, while bus stops and shops have a significant positive impact on motorcycle theft. The residential area has significant positive impacts on both bicycle and motorcycle thefts. (3) The proportion of low-educated has a significant deterrent effect on bicycle theft but a positive impact on motorcycle theft, while the proportion of low-income residents significantly increases motorcycle theft. The proportion of migrant population and residential land area within communities have a significant positive impact on both bicycle theft and motorcycle theft. (4) Surveillance cameras have a significant positive impact on motorcycle theft, but ambient population density has a significant deterring effect on motorcycle thefts. Neither of these two guardianship variables have significant impacts on bicycle thefts.

The main theoretical contribution of this study is that it provided a comprehensive assessment on the contrasting spatial distributions between bicycle thefts and motorcycle thefts and on the contrasting contributing factors for the two thefts. These findings provide a scientific basis for effective crime prevention and urban governance. A uniform strategy would not be able to prevent and reduce both bicycle thefts and motorcycle thefts. Effective strategy should target the high concentration areas and intervene the specific contributing factors for each of the two thefts. Firstly, more resources should be directed to residential areas, especially where the proportion of migrant population is high. Secondly, different preventative strategies will be developed for bicycle thefts and motorcycle thefts. For example, prevention of bicycle thefts should target central urban areas such as car parks, subway stations, and internet cafes, while prevention of motorcycle thefts should focus on bus stops and shops in the suburbs.

Data availability

Due to police department and telecommunications company requirements, the data used in this paper is confidential.

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Author contributions

Lin Liu: Conceptualization, Formal analysis, and Writing. Heng Liu: Software, Model calculation and Writing. Dongping Long: Supervision, Reviewing, and Editing. Xinhua Huang: Software.

Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

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