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A Novel Analytical Framework for Modeling Crime Spatial Patterns Using Composite Urban Environmental Factors

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Abstract

The urban physical environment is composed of multiple elements that collectively influence the spatial pattern of crime. Existing research has predominantly focused on the relationship between individual types of facilities and crime, yet there remains a gap in comprehensively examining the integrated effects of the urban physical environment. This study, taking 87 police precincts in the central city of Changchun as units of analysis, innovatively constructs an integrated "Factor Analysis–Negative Binomial Regression" framework. First, factor analysis is applied to reduce the dimensionality of 14 categories of Points of Interest (POI) data, extracting three comprehensive factors that characterize the macro-level functional structure of the city: the "Business and Economic Activities Factor," the "Residential, Educational, and Transportation Factor," and the "Leisure and Entertainment Factor." This approach effectively addresses the issue of multicollinearity among variables and uncovers the underlying macro-level functional factors. Subsequently, a negative binomial regression model is employed to analyze the impact of each factor on crime counts. The results indicate that: (1) The spatial distribution of urban crime is markedly heterogeneous and is systematically driven by the urban functional structure; (2) Both the "Business and Economic Activities Factor" and the "Leisure and Entertainment Factor" exhibit significant positive effects on crime, with each unit increase in their scores associated with an approximately 20% increase in the relative risk of crime; (3) The influence of the "Residential, Educational, and Transportation Factor" is not significant. Collectively, the findings demonstrate that shifting the perspective from "micro-level facilities" to "macro-level functional dimensions" can provide deeper insights into the fundamental formative mechanisms underlying the spatial pattern of crime.

Keywords: crime geography; routine activity theory; factor analysis; negative binomial regression; China

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1. Introduction

Urban crime remains a significant challenge for city residents and governing bodies, exhibiting marked heterogeneity in its spatial distribution—a phenomenon that has attracted considerable interdisciplinary attention. As a complex social phenomenon, crime is not randomly distributed across space but is profoundly influenced by the urban environment, demonstrating distinct spatial regularities. Existing research has employed multi-scale analytical methods to explore the association between underlying geographical

space and crime distribution [1]. Among the environmental elements affecting the spatial pattern of urban crime, the physical environment, due to its tangible and quantifiable nature, has been widely examined [2,3], emerging as a prominent research focus among the various factors contributing to the spatial differentiation of crime.

Guided by environmental criminology theories, utilizing Point of Interest (POI) data to characterize specific crime-prone places (e.g., commercial centers, transportation hubs, entertainment venues) and investigating their association with crime distribution has become a mainstream research paradigm. Scholars have primarily focused on identifying and extracting crime-prone areas within the urban physical space by targeting intersections of "exposed targets" and "absence of guardianship." However, the "single POI type" analytical paradigm faces challenges when applied to areal spatial units like police precincts or communities. We posit that the spatial pattern of urban crime results from a synthesis of influences, particularly for crime aggregated at areal units (e.g., streets, communities, police precincts). It is difficult to attribute a high crime count within a unit solely to the presence of bars, disregarding the potential roles of convenience stores, hotels, shops, hospitals, logistics stations, and residential buildings. The crime count within an areal unit is more likely the product of the co-existence and interaction of multiple facility types, rather than the independent influence of any single facility type. Furthermore, different urban physical environmental elements do not exist in isolation but are often interrelated and co-located (e.g., residential areas are typically accompanied by dining and retail facilities; shopping malls are often surrounded by bus stops, hotels, and entertainment venues). This leads to significant "multicollinearity" issues at the statistical level, potentially masking underlying dominant factors. Therefore, the reality is more likely that the collective presence of these facilities determines the level of crime risk across different areas. In other words, the volume of criminal activity in a given region is therefore more plausibly the result of the combined effect of these physical elements, or it can be argued that latent factors play a substantive role in shaping the crime spatial pattern.

Consequently, this study argues for a necessary shift in analytical perspective from micro-level, isolated facilities to macro-level, integrated functional dimensions. We propose using factor analysis to extract latent dimensions representing fundamental urban functional structures from diverse POI data, and subsequently testing the systematic driving effects of these macro-functional dimensions on the crime spatial pattern across areal units. This approach helps overcome variable multicollinearity and facilitates understanding the formation mechanisms of crime spatial differentiation from a more fundamental, structural perspective. Specifically, this study aims to address the following questions: 1. Can urban macro-functional factors with clear geographical significance be extracted from comprehensive POI data? 2. How do these macro-functional factors influence crime counts in areal units (police precincts)? To achieve these objectives, this study adopts an integrated "Factor Analysis-Negative Binomial Regression" analytical framework, using 87 police precincts in Changchun City, China, as a case study.

The remainder of this paper is structured as follows: Section 2 presents a literature review, systematically reviewing environmental criminology theories, the application of POI in crime research, and the potential and limitations of factor analysis. Section 3 introduces the study area, data, and methodology. Section 4 presents the research results. Section 5 discusses these findings. Section 6 concludes with the main findings, policy implications, and directions for future research.

2. Literature Review

Understanding the environmental correlates of crime primarily draws upon two classic theories in environmental criminology. Crime Pattern Theory, from a physical environ-

mental perspective, reveals the spatial characteristics of crime-prone places, positing that the activity spaces of potential targets, offenders' cognitive maps, and guardians' behavioral spaces jointly determine crime distribution patterns—all of which are closely tied to the physical environment, as it influences pedestrian flow, visitor types, and surveillance levels [4]. Routine Activity Theory suggests that criminal acts are more likely to occur when a motivated offender, a suitable target, and the absence of a capable guardian converge in time and space. This theory focuses particularly on direct-contact predatory crimes like theft and robbery, which require physical convergence of the three elements [5]. The physical environment is often key in determining this spatio-temporal convergence. Specifically, diverse physical environments typically correspond to differentiated functions, attracting or accommodating populations of varying intensity and scale. This, in turn, leads to pronounced spatial differentiation in crime opportunities formed by the convergence of the three elements. Empirical studies employing comprehensive urban data have further corroborated the significant and intricate role of the physical environment in shaping the spatial pattern of crime [6]. Therefore, based on these theories, identifying crime-prone places in space (where routine activities create more crime opportunities) becomes key to constructing a sound analytical model. These areas can be categorized into three types: 1. Target-rich areas, e.g., commercial centers (shopping malls [7], night markets), transportation hubs (metro stations [8], railway stations), entertainment venues (bars [9–11]), nightclubs, internet cafes [12]). 2. Guardian-absent areas, e.g., abandoned buildings, industrial zone factories [13], poorly lit parks [10,14,15], playgrounds [16], or alleys, old residential communities, highways [10,17], major roads [18,19], secondary roads, branch roads [20,21], boundaries between residential and other land uses [22]. 3. Nodes of routine activity convergence, e.g., commuting routes (bus stops [12,23], parking lots, intercity bus stations [24,25]), schools [16], hospitals [14], shops [26], stadiums [27], banks [13], restaurants [15], barbershops [18], gas stations [28], hotels [9,29], among others. These studies confirm significant associations between specific place types and crime occurrence, indicating that the spatial distribution of crime-prone places largely determines the overall pattern of criminal activity.

With the proliferation of multi-source geospatial data, using POI to quantify crime-prone places and building statistical models linking them to crime counts has become a mainstream research paradigm. However, most existing studies focus on examining the independent effects of single or a few POI types. While this approach helps clarify the effect of specific facilities, it may oversimplify urban environmental complexity. In reality, various facilities often cluster in functionally complementary forms. Therefore, the crime level within an analytical unit (e.g., police precinct, street) is more likely the result of the combined effect of the "environmental mix" constituted by all functional facilities within it, rather than being attributable to a single element. The widespread multicollinearity among variables also suggests the potential existence of deeper, latent structural factors driving the co-distribution of surface-level POI types and ultimately influencing crime risk. To handle high-dimensional environmental variables, machine learning methods are a natural consideration, feeding all elements into computers for prediction and simulation. Recent advances in such methods are notable, e.g., using Random Forest regression models to predict crime and quantify/rank the influence of urban indicators on homicides, grouping them by impact level via clustering [30], deep learning-based rapid detection methods for multi-dimensional feature phishing crime behavior detection [31], and using three machine learning algorithms for comparative analysis of financial fraud behavior prediction [32]. While these methods excel in improving prediction accuracy, they often lack explanatory power, particularly in clarifying relationships between different elements. For mechanism-oriented research aiming to deepen theoretical understanding, a method is needed that

can both effectively reduce dimensionality and yield clear, interpretable results. In this context, classical factor analysis demonstrates unique value. This method can aggregate numerous correlated variables into a few uncorrelated composite factors, revealing latent dimensions driving variable covariation while retaining most original information. By interpreting factor loadings, a multitude of micro-indicators can be synthesized into several environmental constructs with clear socio-ecological meaning. This approach has been successfully applied in human geography [33–37]. However, its application in environmental criminology research remains insufficient. Existing studies either use it merely to handle control variables [38] or solely as a technical tool to address multicollinearity, without deeply exploring the theoretical connotations of the composite factors or their substantive explanatory significance for crime patterns [39]. Systematically employing factor analysis to integrate multiple POI types and distill spatial structural factors influencing crime remains an under-explored research direction.

Regarding the modeling strategy, because crime count data are typically over-dispersed, the standard Poisson regression is often inadequate. The Negative Binomial regression model, which introduces a dispersion parameter, effectively handles this issue and has thus become a robust standard in spatial crime analysis [40–43]. Therefore, this study adopts an integrated 'Factor Analysis–Negative Binomial Regression' framework to first identify structural factors and then rigorously quantify their impacts.

In summary, the existing literature has laid a solid theoretical foundation and accumulated substantial empirical evidence for exploring the spatial patterns of urban crime and their environmental causes, alongside developing a range of mature analytical methods. However, current research still faces limitations in perspective and methodological challenges regarding how to systematically characterize and integrate multidimensional, collinear urban physical environmental information. This constitutes precisely the entry point for this study's proposed breakthrough: by integrating factor analysis and negative binomial regression models, we first extract composite factors representing the deep structure of the urban environment from multi-type POI data, then rigorously test their influence within a regression framework. This research path aims to move beyond examining isolated environmental indicators, seeking a more comprehensive and profound understanding of the driving mechanisms behind crime spatial differentiation from the holistic dimension of urban socio-ecological structure. This endeavor is intended to provide more systematic scientific evidence for crime prevention and spatial governance based on environmental design.

3. Materials and Methods

3.1. Study Area

The study area for this paper is Changchun City, located in central Northeast China and the north-central part of Jilin Province (43°05′~45°15′ N, 124°18′~127°05′ E). As the capital of Jilin Province, a sub-provincial city, and one of the important central cities in Northeast China, it lies at the geographical center of the region. The total administrative area of Changchun City is 24,744 km^2, with a permanent resident population of 9.1019 million at the end of 2022 and an urbanization rate of 68.2%. It is a significant industrial city and China's "Automobile City". The spatial analysis units for this study are defined as the jurisdictions of police stations within the main urban area of Changchun (hereinafter referred to as "police precincts"), excluding Jiutai District, Shuangyang District, and peripheral county-level administrative divisions. The study scope also encompasses townships surrounding the main urban area that are closely connected to the core and have been incorporated into the main urban jurisdiction. Ultimately, 87 police precincts within Changchun's main urban area were identified as the study units (see Figure 1).



Figure 1. Location of the study area in Changchun City, Jilin Province (left).

3.2. Data Sources

The core data for this study include crime data, spatial boundary data, and Points of Interest (POI) data. The sources and characteristics of each dataset are as follows:

Crime Data, Police Precinct Boundary Data, and Population Statistics: These were obtained from the Changchun Public Security Bureau. The crime data consist of recorded criminal cases for each police precinct in 2019, totaling 14,712 valid crime records. The spatial boundary data for the police precincts accurately define the geographical extent of the 87 analysis units. Based on the data we collected, the overall crime rate in Changchun City in 2019 was 4.95 per 1000 residents.

POI Data: these were acquired via the Baidu Maps API for 2019, focusing on 14 categories of facilities potentially associated with crime. These categories include KTVs, Residential Areas, Bus Stops, Companies & Enterprises, Shopping & Retail, Financial Services, Bars, Hotels & Hostels, Catering Services, Infrastructure, Leisure & Entertainment, Medical Services, Government Institutions, and Educational Institutions, totaling 131,122 data points.

4. Research Methods

4.1. Location Quotient

To reveal the uneven spatial distribution and agglomeration characteristics of criminal activity in Changchun and to mitigate the influence of differences in base numbers such as area and population across police precincts, this study employs the Location Quotient (LQ) to standardize the raw crime count data, thereby accurately measuring the relative concentration of criminal activity. The core concept of LQ is to compare the proportion of a specific element within a particular analysis unit to its proportion in the entire study area. An LQ value greater than 1 indicates that the element is relatively concentrated within the study unit, while a value less than 1 suggests it is relatively dispersed. In this study, the LQ is calculated using the following formula:

$$LQ_{i(pop)} = \frac{\left(\frac{c_i}{P_i}\right)}{\left(\frac{C_{total}}{P_{total}}\right)} \quad (1)$$

where: $LQ_{i(pop)}$ presents the crime location quotient for the i-th police precinct, using population as the base. c_i denotes the number of criminal cases in the i-th police precinct. P_i represents the population of the i-th police precinct. C_{total} denotes the total number of criminal cases in the entire central urban study area of Changchun. P_{total} represents the total population of the entire central urban study area of Changchun.

4.2. Factor Analysis

To address the potential issue of multicollinearity among the 14 initial variables and to systematically and comprehensively consider the complex composition of the built environment, thereby delving into the underlying decisive common factors, this study employs Exploratory factor analysis. The core idea of this method is to group variables based on the strength of their correlations, such that variables within the same group are highly correlated while those in different groups have low correlations. Each group of variables represents a latent "common factor." Extracting these common factors achieves data dimensionality reduction and core information extraction, synthesizing multiple specific built environment indicators into a few composite dimensions with clear geographical significance, thus simplifying the analysis of complex problems.

The implementation of factor analysis follows these steps:

Tests for Suitability: The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity are used to verify whether the data meet the conditions for factor analysis. The data are considered suitable for factor analysis when the KMO value is >0.7 and Bartlett's test yields a significance level of $p < 0.05$.

Extraction of Common Factors: The Principal Component Analysis (PCA) method is used to extract common factors. The number of initial common factors is determined based on the "eigenvalue greater than 1" criterion.

Factor Rotation and Naming: The Varimax Rotation method is applied to the factor loading matrix to achieve a clearer factor structure. Based on the principle of "absolute factor loading value > 0.7," the extracted common factors are named and interpreted according to the geographical connotations of the variables with high loadings, thereby defining the composite dimensions of the physical environment.

4.3. Negative Binomial Regression Model

Given the potential spatial dependence inherent in crime data, we conducted a Moran's I test on the model residuals after estimation to assess whether spatial autocorrelation was adequately controlled for in the specification. Since crime count is a type of count variable and typically exhibits over-dispersion (where the variance significantly exceeds the mean), the standard Poisson regression is often inadequate. In contrast, this study employs a negative binomial regression for modeling. This method introduces a dispersion parameter on the basis of the standard Poisson regression, allowing for a more flexible description of the relationship between variance and mean, thereby effectively mitigating estimation biases and underestimation of standard errors caused by over-dispersion. Based on these considerations, this study applies factor analysis to reduce multiple built-environment POI indicators into several principal factors. These factors are mutually independent, effectively addressing multicollinearity among the independent variables, and each represents a comprehensive dimension of the physical environment. They are incorporated as core independent variables into the negative binomial regression model. Additionally, to control for the baseline effect of varying population sizes across police districts on crime counts, population size is included in the model as an offset term. The model is formulated as follows:

$$Yi \sim NB(\mu_i, \theta) \quad (2)$$

$$ln(\mu_i) = \beta_0 + \beta_1 F_{1i} + \beta_2 F_{2i} + \cdots + \beta_k F_{ki} + ln(P_i) + \varepsilon_i \quad (3)$$

where: Yi is the crime count in the i-th police precinct, assumed to follow a Negative Binomial distribution; θ is the dispersion parameter. μ_i is the conditional expected value of the crime count for the i-th police precinct. β_0 is the intercept term of the model. $F_{1i}, F_{2i}, \cdots, F_{ki}$ represent the scores of the 1st, 2nd, . . ., kth physical environment principal factors (extracted from the original POI data via factor analysis) for the i-th police precinct. $\beta_1, \beta_2, \cdots, \beta_k$ are the regression coefficients to be estimated, measuring the direction and magnitude of the effect of each principal factor on the crime rate. $ln(P_i)$ is the offset term based on population, whose coefficient is fixed at 1, used to control for differences in population size across police precincts. P_i is the population of the i-th police precinct. ε_i represents the random error term.

5. Research Results

5.1. Spatial Autocorrelation Test Results of Crime Counts

Prior to conducting the core spatial analyses and regression modeling, we first assessed whether the dependent variable—crime count across the 87 police precincts—exhibits spatial autocorrelation. This step is crucial because significant spatial dependence would necessitate the use of spatial regression models to avoid biased estimates. We employed Global Moran's I to test for global spatial autocorrelation, using a queen contiguity spatial weights matrix to define neighboring relationships among the precincts.

The test results yielded a Moran's I index of 0.002 with a p-value of 0.531. Since the p-value exceeds the conventional significance level of 0.05, we conclude that the spatial distribution of crime counts does not exhibit statistically significant global spatial autocorrelation. This indicates that crime counts in one precinct are not systematically influenced by crime counts in neighboring precincts, and the spatial pattern is relatively random in terms of large-scale clustering.

Given the absence of significant spatial dependence, the use of a non-spatial Negative Binomial regression model is methodologically appropriate. Our modeling strategy, therefore, focuses on explaining crime variation through the composite functional factors of the built environment without introducing spatial lag or error terms.

5.2. Spatial Distribution Characteristics of Crime Location Quotient in Changchun

The spatial differentiation of the crime Location Quotient in Changchun is significant (as shown in Figure 2), exhibiting an overall pattern of a gradient decrease from the core functional areas towards the periphery. The distribution characteristics of high LQ areas primarily manifest in the following aspects: (1) Police precincts containing important commercial agglomerations typically exhibit higher crime risks. Areas ①, ②, ③, and ④ in Figure 2 correspond to locations of four major commercial agglomerations in Changchun. It is highly probable that the high crime risk in these precincts is directly associated with these commercial centers, which aligns with findings from existing studies. (2) Police precincts containing large-scale commercial complexes or major markets are also areas with relatively high crime risk. For instance, areas ⑤ and ⑥ correspond to the locations of the Ouya Mall and the Zhongdong Market (a super-large shopping center and a wholesale market, respectively). Although these areas are not conventionally recognized as central business districts, it is reasonable to suspect that their relatively high crime risk may be linked to the presence of these large commercial entities. (3) The high crime risk observed in other areas, such as ⑥ and ⑦, might be related to their specific regional attributes. These areas concentrate high-tech industries, universities, as well as cultural tourism, and leisure entertainment facilities. It is likely that the combination of these factors collectively contributes to the increased crime risk. In summary, while Figure 2 allows for the tentative

identification of potential drivers of increased crime risk, these associations are largely based on empirical observation. Given the multitude of interconnected factors influencing the spatial variation in crime risk and the significant heterogeneity of influencing factors across different areas, deeper insights cannot be gleaned from spatial distribution maps alone. It is necessary to establish an inclusive and comprehensive analytical model for mathematical exploration to genuinely understand the influencing factors of the spatial crime pattern.

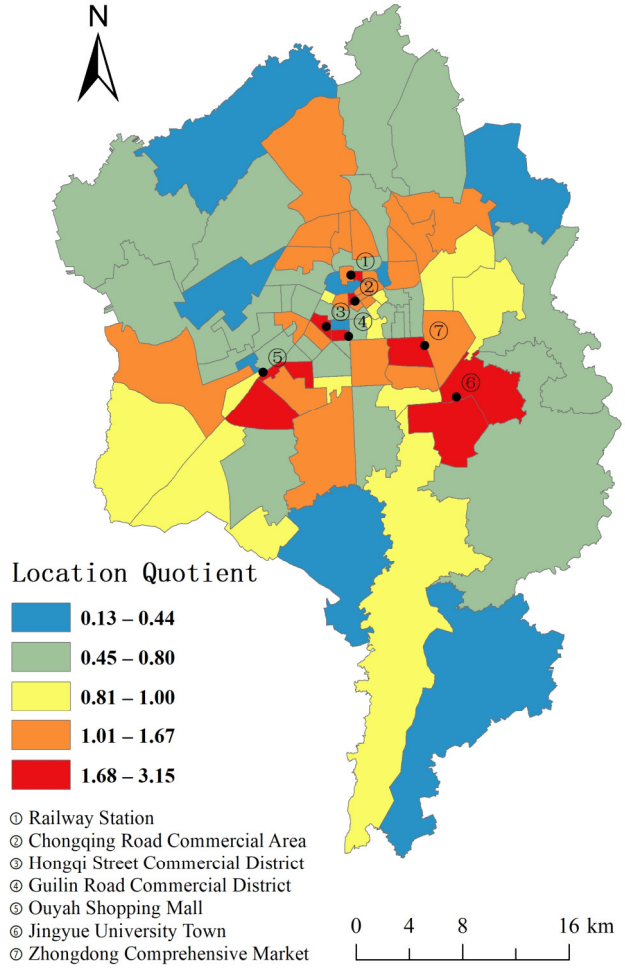

Figure 2. Location Quotient of Crime and Its Spatial Distribution.

5.3. Results of Factor Analysis on Urban Physical Environment

This study employed factor analysis to extract latent driving factors from 14 initial variables, aiming to systematically reveal the composite structure of Changchun's physical environment. First, the 14 indicators were standardized using the Z-score method to eliminate the influence of differing measurement units. Subsequently, factor analysis was conducted using SPSS 27.0 software. The suitability tests yielded a KMO statistic of 0.807 (>0.7, suitable for factor analysis) and a Bartlett's Test of Sphericity p-value of 0.000 (<0.001), indicating significant correlations among the variables and confirming the data's suitability for factor analysis. Principal Component Analysis was used to extract common factors. Following the dual criteria of "eigenvalue > 1" and "cumulative variance contribution rate > 70%", three common factors were retained. The Varimax rotation method was applied to the factor loading matrix to enhance interpretability. As shown in Table 1, the eigenvalues of the first three common factors were all greater than 1, and their cumulative variance contribution rate reached 72.493% (>70%), indicating that these three factors

explain most of the variable information. The variance contributions of the rotated factors became more balanced, meeting the analysis requirements. Based on the rotated factor loadings (Table 2) and the specific connotations represented by the variables with high loadings, the three common factors were named "Business and Economic Activities Factor", "Residential, Educational and Transportation Factor", and "Leisure and Entertainment Factor". This process successfully synthesized 14 interrelated POI variables potentially related to crime spatial distribution in Changchun into three common factors, achieving a transition from micro-level indicators to meso-level theoretical dimensions. Finally, a comprehensive factor score was calculated using the variance contribution rates of each factor as weights, providing independent variables for subsequent regression analysis.

Table 1. Total Variance Explained in Factor Analysis.

Component	Initial Eigenvalues			Extracted Sum of Squared Loadings			Rotated Sum of Squared Loadings		
	Total	% of Variance	Cumulative%	Total	% of Variance	Cumulative%	Total	% of Variance	Cumulative%
1	7.418	52.984	52.984	7.418	52.984	52.984	3.851	27.504	27.504
2	1.516	10.829	63.813	1.516	10.829	63.813	3.266	23.332	50.836
3	1.215	8.680	72.493	1.215	8.680	72.493	3.032	21.657	72.493
4	0.871	6.219	78.712						
5	0.676	4.830	83.542						
6	0.592	4.231	87.772						
7	0.544	3.886	91.659						
8	0.404	2.884	94.543						
9	0.220	1.572	96.115						
10	0.201	1.433	97.548						
11	0.131	0.936	98.484						
12	0.099	0.710	99.194						
13	0.071	0.506	99.700						
14	0.042	0.300	100.00						

Table 2. Rotated Factor Loading Matrix.

	Principal Factor 1	Principal Factor 2	Principal Factor 3
KTV	0.386	0.092	0.619
Residential Areas	0.228	0.863	0.261
Bus Stops	0.222	0.725	−0.194
Companies and Enterprises	0.761	0.244	−0.048
Retail Stores	0.844	0.106	0.152
Financial Services	0.507	0.367	0.580
Bars	−0.053	−0.108	0.806
Hotels and Guesthouses	0.664	0.086	0.278
Catering Services	0.543	0.493	0.612
Daily Life Services	0.773	0.386	0.312
Leisure and Entertainment	0.341	0.431	0.753
Medical Services	0.603	0.489	0.405
Government Agencies	0.475	0.492	0.461
Educational Institutions	0.109	0.847	0.196

Specifically, Principal Factor 1 had high loadings on variables such as Companies & Enterprises, Shopping & Retail, Hotels & Hostels, Life Services, and Medical Services. These variables primarily reflect urban economic and service functions, such as generating economic output, absorbing employment, and providing daily services. Therefore, it was named the "Business and Economic Activities Factor".

Principal Factor 2 had high absolute loadings on variables including Residential Areas, Bus Stops, and Educational Institutions. These variables primarily reflect functions related

to residential life, school education, and public transportation. Therefore, it was named the "Residential, Educational, and Transportation Factor".

Principal Factor 3 had high absolute loadings on variables including KTVs, Bars, Catering Services, and Leisure & Entertainment. These variables primarily reflect the agglomeration characteristics of entertainment and leisure venues. Therefore, it was named the "Leisure and Entertainment Factor".

Subsequently, we extracted these three principal factors for Changchun City via factor analysis and computed their factor scores. The spatial distribution of these three principal factors, as shown in Figure 3, reveals distinct functional differentiation characteristics:

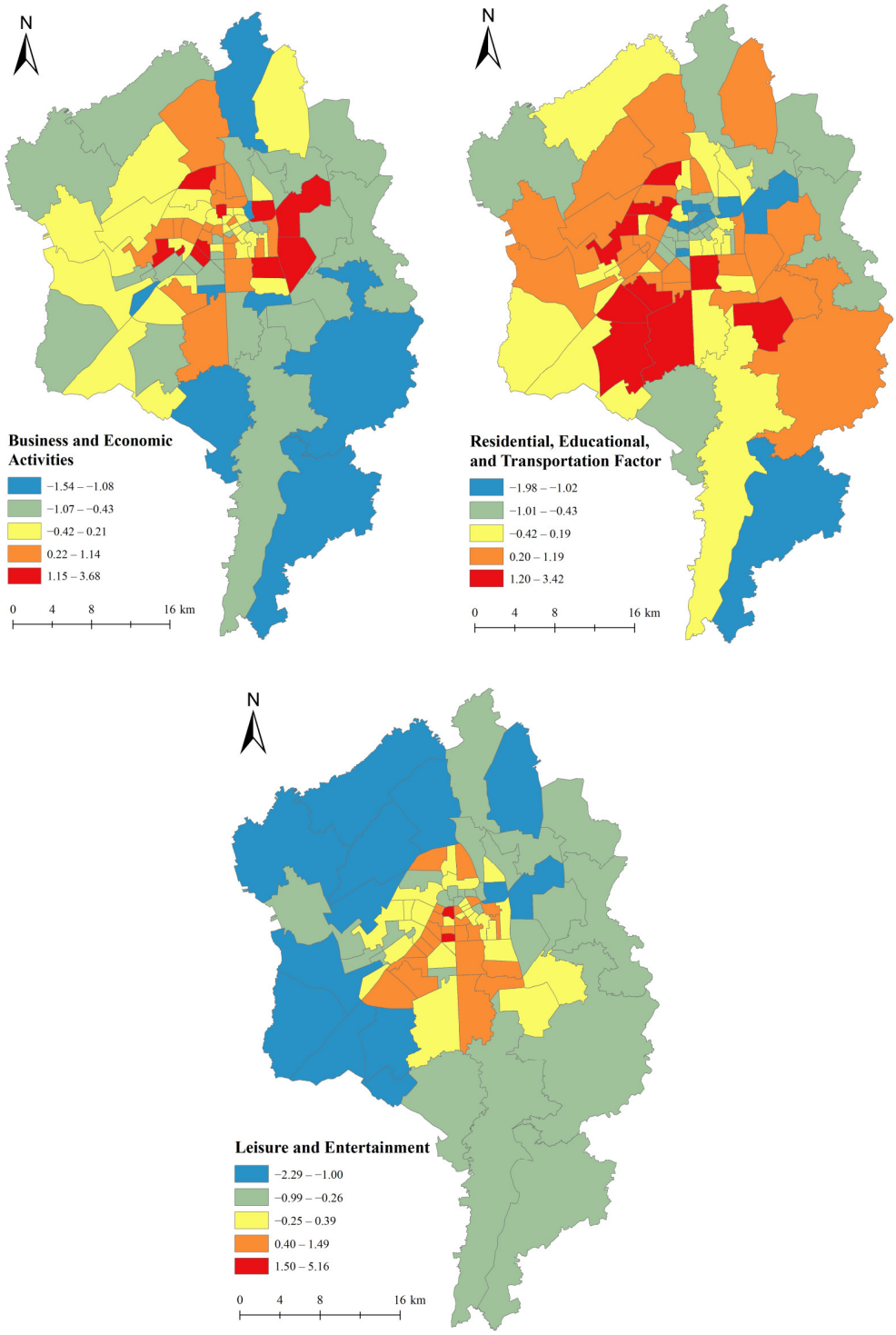

Figure 3. Spatial Distribution of the Three Comprehensive Factor Scores.

The Business and Economic Activities Factor generally exhibits a distribution pattern of high values in the central area and low values in the periphery. Several high-value clusters are concentrated in areas such as the railway station, the Hongqi Street commercial district, and industrial development zones with concentrated companies and enterprises (e.g., the Changchun Automobile Industry Development Zone and the Economic and Technological Development Zone). These areas are characterized by a high concentration of economic production, employment, and comprehensive services.

The Residential, Educational and Transportation Factor score generally shows a pattern of lower values in the center and higher values on the periphery. High-value areas are mainly located in residential areas on the urban periphery (especially in the west and south) and areas with concentrated universities (primarily in the southwest and southeast). This reflects the dominance of residential, educational, and public transport service functions in these areas.

The distribution of the Leisure and Entertainment Factor score shows a more pronounced central agglomeration pattern. Its high-value areas are primarily concentrated in the city center, such as the Chongqing Road and Guilin Road areas, which are rich in leisure and entertainment resources.

Overall, as Changchun is a manufacturing-oriented industrial city that has developed through mono-centric sprawl, the spatial distribution of its urban functions presents a relatively clear core-periphery structure with distinct functional zoning, which likely largely determines the basic distribution characteristics of the crime pattern.

5.4. Negative Binomial Regression Model Results: Impact Effects of Urban Physical Environment Factors on Crime Spatial Differentiation

Given that the crime counts across Changchun's police precincts also exhibit over-dispersion (variance much larger than the mean), this study constructed a Negative Binomial Regression model to explore the impact of the composite urban physical environment factors on the spatial distribution of crime counts. The model incorporated the logarithm of the population in each police precinct as an offset term to control for the population base effect, thereby assessing the influence of each principal factor. The core independent variables were the three urban physical environment principal factors extracted from the factor analysis (Business and Economic Activities Factor, Residential, Educational, and Transportation Factor, Leisure and Entertainment Factor). The regression results are presented in Table 3.

Table 3. Results of Negative Binomial Regression Model.

Variable	Coefficient	IRR	Std. Error	z-Value	*p*-Value
(Intercept)	3.87040	47.96	0.05066	76.397	$<2 \times 10^{-16}$ ***
Business and Economic Activities	0.18541	1.204	0.05085	3.646	0.000266 ***
Residential, Educational, and Transportation Factor	0.07253	1.075	0.05073	1.430	0.152804
Leisure and Entertainment	0.18532	1.204	0.05074	3.652	0.000260 ***
Model Fit Indices	Nagelkerke's R^2 = 0.377			AIC = 987.12	
	Null deviance 119.066 (df = 86)			Residual deviance 90.349 (df = 83)	

Note: *** indicates that $p < 0.001$, and no mark indicates that $p > 0.05$.

5.4.1. Model Fit Assessment

The calculation confirmed significant over-dispersion in the urban crime data (dispersion parameter Theta = 4.641, Std. Error = 0.709; its reciprocal is significantly non-zero), validating the suitability of the Negative Binomial model over the Poisson model. The

Nagelkerke's R^2 was 0.377, indicating that the three physical environment principal factors collectively explain 37.7% of the spatial variation in crime counts, playing a key role in shaping the spatial crime pattern. Furthermore, the residual deviance (90.349) decreased significantly from the null deviance (119.066) (with a reduction of 3 degrees of freedom), further illustrating that the included physical environment factors have a collectively significant explanatory power for crime counts.

5.4.2. Analysis of the Impact Effects of Urban Physical Environment Factors

Business and Economic Activities Factor: The regression coefficient is 0.185 ($p < 0.001$), statistically significant. Holding other factors constant, a one-unit increase in this factor score is associated with an approximately 20% increase in the relative risk of crime (IRR = $e^{0.185} \approx 1.204$). This result confirms a direct association between the spatial distribution of urban economic production, commercial activities, and various comprehensive service functions and an increase in crime risk. As this factor aggregates facilities such as companies & enterprises, shopping & retail, life services, hotels & hostels, and medical services, it essentially represents the concentration of urban economic vitality (particularly daytime economic activity) and comprehensive service functions. Areas with high scores on this factor are often characterized by a high mix of urban functions and dense commercial and service activities (e.g., core commercial streets, comprehensive service nodes). These areas, due to high pedestrian flow, increased target exposure, and strong spatial anonymity, can significantly elevate crime opportunities, thereby increasing crime risk.

Residential, Educational, and Transportation Factor: The regression coefficient is 0.073 ($p = 0.153$), not statistically significant. This indicates that urban functions such as residence and education do not have a significant effect on criminal activity overall. In other words, from a macro perspective, the realization of these functions is not a primary influencing factor in the formation of the overall spatial crime pattern. Areas with high scores on this factor are typically dominated by large residential areas or concentrated university districts. Although an increase in residential population and housing might increase the potential for certain crimes like burglary, this effect might be counterbalanced by informal social control within the community (e.g., neighborly watchfulness).

Leisure and Entertainment Factor: The regression coefficient is 0.185 ($p < 0.001$), similar in magnitude and significance to the Economic and Comprehensive Service Factor. A one-unit increase in this factor score is also associated with an approximately 20% increase in the relative risk of crime (IRR $\approx$ 1.204). The spatial distribution of urban recreation and leisure functions also plays a fundamental role in shaping the urban crime spatial pattern. Agglomerations of entertainment and leisure (e.g., entertainment districts within commercial areas, nightlife hubs) are significant generators of crime "hotspots". As this factor represents the concentration of economic formats such as KTVs, bars, catering, and leisure & entertainment (particularly the nighttime economy), from the perspective of the "Routine Activity Theory" in criminology, such areas likely amplify crime risk by simultaneously converging the three elements of crime–"motivated offenders, suitable targets, and the absence of capable guardians"–due to factors like nighttime crowds, weakened social guardianship, and alcohol consumption.

The spatial heterogeneity of crime incidence in Changchun is structurally driven by the urban physical environment, yet its influence demonstrates distinct dimensional variations. Specifically, economic activities and commercial services (representing the core of daytime economic vitality) and recreation and leisure facilities (constituting the core of nocturnal social vibrancy) emerge as key environmental dimensions that significantly elevate crime risk. These factors influence crime distribution by shaping spatial contexts characterized by high opportunity and low guardianship. Conversely, the residential and

scientific-educational factors exhibited no independent significant effect. This finding robustly corroborates the central tenet of Crime Pattern Theory—that specific physical environments, by molding the spatiotemporal characteristics of human routine activities, become critical arenas for criminal opportunities and risks [44,45].

6. Discussion

Prior research on the spatial pattern of crime and its influencing factors has predominantly focused on specific types of urban facilities (e.g., bars, internet cafes, bus stops) to explain spatial crime variation. While this paradigm has been invaluable in identifying specific crime generators or crime attractors, its utility becomes constrained when analyzing crime aggregated at areal units, where the complex interplay of multiple facilities must be considered. In the intricate fabric of real urban environments, various physical elements do not exist in isolation; rather, they are organized in a highly synergistic and structured manner. This structure resonates with the fundamental urban functions—living, working, recreation, and circulation—as outlined in the seminal planning document, the Athens Charter. When research is conducted at the scale of areal units such as neighborhoods, police precincts, or communities, the crime count within each unit represents a comprehensive social outcome arising from this complex internal functional structure. A high-crime area is seldom the result of a single bar or a dark alley in isolation; it is more likely determined by a foundational risk landscape, underpinned by the dominant functional attributes—collectively represented by multiple facilities—that the area supports.

Consequently, this study introduces factor analysis to effect a crucial shift in perspective: moving the focus from 14 discrete and collinear specific POI indicators to three independent latent dimensions that capture the core functional spatial structure of Changchun. These dimensions—the "Business and Economic Activities Factor" (corresponding to employment, commerce, and service functions), the "Residential, Educational, and Transportation Factor" (corresponding to residential, educational, and public transport functions), and the "Leisure and Entertainment Factor" (corresponding to recreational functions)—are not merely products of data reduction. They constitute effective measurements of the deep-seated functional structure of urban space. Our negative binomial regression results demonstrate that these macro-level, structural functional dimensions might exert a fundamental and critical shaping role, operating above the population base to delineate the underlying skeleton of urban crime spatial differentiation.

From a theoretical perspective, routine activity theory in environmental criminology posits that crime occurrence requires the convergence in time and space of a "motivated offender," a "suitable target," and the "absence of a capable guardian." While Routine Activity Theory has been predominantly applied to elucidate the spatiotemporal patterns of crime occurrence (i.e., where and when), its potential in uncovering the deeper, structural urban functional underpinnings that give rise to these very patterns has been less explored. Our findings suggest that the city's fundamental functional layout may constitute the structural underpinnings that shape this "latent propensity". In other words, the functional dimensions extracted in our study provide clues to the question of why certain areas inherently possess a latent tendency to converge these three elements. The significant positive association of the "Business and Economic activities" as well as "Recreation and Leisure" factor scores with crime can be attributed to their propensity to create spatial contexts characterized by "high opportunity and low guardianship" while fulfilling their primary functions. This finding aligns closely with studies in Western cities, suggesting that Brantingham & Brantingham and Bernasco have consistently identified commercial and entertainment districts as typical crime hotspots [4,18].

Areas concentrated with economic and comprehensive services (e.g., Central Business Districts, corporate hubs, commercial streets) attract massive human flows and material wealth (high density of "suitable targets") through intensive job opportunities and commercial offerings. Simultaneously, the anonymity and crowd aggregation in these spaces often weaken informal social control, objectively creating more opportunities for crime. Functional zones dominated by recreation and leisure (e.g., restaurant and bar streets, KTV clusters) are focal points of nocturnal urban vitality. They not only attract people seeking entertainment (among whom "motivated offenders" may be present) but also create typical conditions of "absent guardianship" due to factors like alcohol consumption, the nighttime environment, and lowered vigilance among patrons. The significance of these two factors indicates that the spatial pattern of crime is superimposed upon a macro-level geographical structure of human, material, and activity flows determined by the city's economic and entertainment functions. Crime emerges as a byproduct of the vitality inherent to these specific urban dimensions, an 'ecological risk' innate to these particular functional areas.

In contrast, the non-significant relationship between the "Residential, Education, and Transportation Factor" and crime likely stems from the tendency of residential and campus areas to be more enclosed, stable, and homogeneous in function. Activity patterns here are more regular, social networks are tighter, and residents/students tend to exhibit higher vigilance towards "strangers" (i.e., stronger informal social control). This functional attribute inherently constructs a "structural stability" that acts as a defensive mechanism. It does not generate—and may even repel—the convergence of the three elements of Routine Activity Theory. Consequently, even though property as targets exists in these areas, the crime risk is neutralized by the stability conferred by their overall functional structure. This further underscores that the overall spatial crime pattern is more strongly associated with the distribution of urban economic/comprehensive service and leisure/entertainment functions.

For aggregated areal data like police precincts, traditional "single-POI-count" models suffer from a fundamental flaw: they attempt to explain a macro-level, areal phenomenon using micro-level, point-based explanations, inevitably inducing a problem of scale mismatch. In contrast, the "latent factors" extracted via factor analysis capture the overall functional property at the precinct scale, achieving analytical scale alignment with the aggregate crime level we seek to explain. Furthermore, this approach effectively isolates the common driving force—the fundamental urban function—behind facilities that are inherently co-located in reality and statistically collinear (e.g., malls and restaurants, bars and KTVs). This allows us to identify that it is the "Recreation and Leisure" functional dimension that influences the crime pattern, moving beyond disentangling the individual contributions of "bars" versus "KTVs." Therefore, we propose that when dealing with aggregated spatial data, shifting the analytical focus from micro-facilities to macro-functional dimensions represents a critical theoretical and methodological advancement that allows for a more systematic understanding of how urban functional environments shape crime opportunity structures. It enables us to transcend fragmented explanations for specific crime locations and instead discern the deep, structural, internal drivers—rooted in urban function—that shape the crime risk level of an entire area. This represents a paradigm shift from a piecemeal analysis of "how the count of a specific POI type affects crime" towards a systematic consideration of "how a specific type of comprehensive urban functional environment shapes the opportunity structure for crime," offering a paradigmatic methodological innovation for geographical criminology.

In this study, various crime types were aggregated into a total crime count for analysis, which seeks to elucidate the overall and structural influence of the city's foundational functional layout on criminal opportunity generation. This approach is premised on the understanding that although specific mechanisms may differ across crime types—such as

theft, robbery, and assault—their spatial opportunity structures are profoundly shaped by the macro-level functional configuration of the urban environment, as supported by the literature [46–48]. For instance, commercial-economic zones and leisure-entertainment districts create an environment characterized by "high opportunity and low guardianship" for multiple crime types by concentrating people and property while reducing levels of informal surveillance. Admittedly, such aggregation may, to some extent, obscure more nuanced associations between specific crime types and particular environmental factors. For example, the non-significant effect of the "Residential, Educational, and Transportation Factor" may reflect its neutral net impact on overall crime: strong informal social control in residential areas could suppress burglary, whereas the population concentration in such areas might increase opportunities for certain contact crimes, with the two effects potentially offsetting each other. Future research could build upon this framework by further disaggregating crime types to uncover more detailed mechanisms.

7. Conclusions

This study, employing the central city of Changchun as a case study, systematically investigates the relationship between the multidimensional structure of the urban physical environment and spatial crime variation by constructing an integrated "Factor Analysis–Negative Binomial Regression" analytical framework. This framework synthesizes disparate, micro-scale POI facilities into distinct "urban functional dimensions" with clear geographical significance, accomplishing a critical shift in analytical perspective from "isolated facilities" to "integrated structure." The research demonstrates that integrating factor analysis with count models can effectively address issues of variable multicollinearity and data over-dispersion prevalent in geographical criminology research.

Through factor analysis, 14 categories of POIs in Changchun were consolidated into three core functional dimensions: "Business and Economic Activities" "Leisure and Entertainment" and "Residential, Education and Transportation" The negative binomial regression results clearly demonstrate that the first two dimensions—particularly economic and recreational functions—exhibit a more pronounced relationship with the spatial pattern of crime, whereas the functional configuration of residential, educational, and transportation areas shows no significant association. This finding provides strong empirical support for core tenets of Crime Pattern Theory and Routine Activity Theory. It underscores that urban functional areas characterized by high-intensity, highly mixed, and anonymous social activities systematically shape "crime opportunities," thereby forming the foundational fabric of urban crime risk.

The primary contribution of this study lies in providing a theoretical framework and methodological toolkit for understanding spatial crime patterns through the lens of fundamental urban functions. It suggests that effective spatial crime governance should also focus on optimizing the layout and management of urban functions. Specifically, based on the finding that the "Leisure and Entertainment" and "Business and Economic Activities" functional dimensions significantly elevate crime risk, urban planning could adopt a dual strategy. First, consider dispersing large-scale nightlife and entertainment clusters to avoid over-concentration of crime opportunities. Second, in unavoidable high-risk zones, implement targeted situational crime prevention—such as enhanced lighting, surveillance, and coordinated management—to mitigate the convergence of offenders, targets, and low guardianship. These evidence-based measures translate macro-functional insights into actionable spatial governance. Future research, guided by this structural perspective, should seek to deepen and broaden understanding by incorporating more diverse datasets and conducting cross-city comparative analyses.

This study has several limitations. First, the characterization of the urban physical environment relies primarily on POI data, and the analytical model examines only the association between the extracted principal factors and crime. While the use of POI data offers advantages in objectively and finely depicting the functional layout of the built environment, and facilitates data processing like factor analysis due to uniform variable types, it must be acknowledged that other physical environmental variables, such as road network density, accessibility, and nighttime lighting levels, could also be critical factors influencing criminal activity [49–51]. Furthermore, substantial theoretical and empirical evidence indicates that social variables, including demographic composition and socio-economic conditions, potentially exert significant influences on the spatial crime pattern [52,53]. This suggests a hierarchical explanatory framework, in which the macro-functional structure of the city forms the foundational risk landscape, while socio-ecological factors may operate by moderating or amplifying crime risks on this basis. The omission of these variables may partly explain why our model accounts for only 37.7% of the variance in crime spatial distribution. It must be acknowledged that while POI data effectively capture the distribution and mix of service facilities, they inherently lack the granularity to represent critical micro-environmental features such as street network accessibility, nighttime lighting, surveillance coverage, or physical decay of buildings. The omission of these variables, which are known to directly influence offender perceptions and guardianship levels, may introduce a potential bias by attributing crime variation solely to macro-functional factors, thereby overlooking the nuanced moderating effects of the immediate physical setting. We emphasize that the core objective of this study was to reveal a more fundamental, foundational risk landscape shaped by the macro-functional structure of the city. Future research, given data availability, could build upon this "functional dimension" foundation by incorporating the aforementioned physical and social environmental variables to construct a more multi-dimensional and multi-tiered analytical framework for a finer-grained explanation and prediction of crime spatial patterns. Moreover, this study employed an aggregated crime count without distinguishing between different crime types. Although this approach helps capture the overall structure of criminal opportunities from a macro-functional perspective, future research analyzing disaggregated crime data would provide more nuanced mechanistic explanations. Finally, relying solely on cross-sectional data from 2019, this study cannot uncover dynamic causal relationships. Subsequent research employing longitudinal designs with longer time-series data and comparative case studies across cities of varying sizes and types would be invaluable for verifying the robustness and generalizability of our findings, providing a clear directive for future inquiry.

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