# Innovation Factor Mobility and Urban Function Optimization: Evidence from the Beijing-Tianjin-Hebei Urban Agglomeration

Yuyu Song<sup>1,a</sup>, Zehui Cui<sup>1,b,\*</sup>

<sup>1</sup>School of Economics, Beijing Wuzi University, Beijing, China <sup>a</sup>yysong799@163.com, <sup>b</sup>zzzh000210@163.com \*Corresponding author

Abstract: Since the implementation of the coordinated development strategy in the Beijing-Tianjin-Hebei (BTH) region, notable progress has been made in constructing a market-oriented system for scientific and technological innovation. However, issues such as uneven distribution of innovation factors and insufficient regional sharing of innovation outputs persist. Moreover, the lack of distinctive functional positioning among cities and an underdeveloped regional division of labor have hindered coordinated innovation. This study analyzes the flow of R&D personnel and funding across 13 BTH cities from 2010 to 2020 using a modified gravity model. It further examines the urban functional specialization pattern through a functional specialization index and evaluates the spatial impact mechanism of innovation factor flows on urban function optimization via a Spatial Durbin Model (SDM). Results reveal a "core-periphery" structure, with innovation factors highly concentrated in Beijing and Tianjin, while surrounding Hebei cities lag behind in specialization. The findings demonstrate that both R&D personnel and funding significantly promote the specialization of production, R&D, and management functions, though spatial spillover effects are uneven. The paper offers empirical evidence and policy implications for enhancing functional differentiation and promoting balanced regional development in urban agglomerations.

**Keywords:** Beijing-Tianjin-Hebei Coordination; Innovation Factor Flow; Urban Function Optimization; Spatial Durbin Model

#### 1. Introduction

Promoting the development of new, high-quality productive forces tailored to local conditions and advancing the integration of technological and industrial innovation are essential for optimizing China's economic structure and fostering new growth drivers. In today's increasingly interconnected global urban network, innovation factors such as technology, capital, and talent circulate and agglomerate with unprecedented efficiency. Within this geographically embedded network, the functional status of cities is increasingly determined by the scale, intensity, and outcomes of innovation factor inflows and outflows.

The Beijing-Tianjin-Hebei (BTH) region, a vital growth pole of China's economy and a national demonstration zone for coordinated innovation, plays a central role in enhancing the country's global competitiveness and establishing an innovation hub. Deng et al (2023) conducted an empirical study on innovation factor allocation and high-quality economic development in the BTH region from 2010 to 2020. The results revealed a continuous upward trend in innovation factor allocation across the three regions. While Beijing demonstrated relatively efficient technological innovation output, Tianjin and Hebei experienced redundancy in input and insufficient output. Nonetheless, both regions are currently in an expansion stage of scale returns (Huang & Liu 2020). Total Factor Productivity (TFP) in the BTH region has slightly improved, with technical efficiency and technological progress serving as key drivers. Government innovation investment shows a nonlinear inverted U-shaped relationship with the urban technological progress index, suggesting that while short-term investment can stimulate innovation, long-term investment may lead to diminishing returns or crowding-out effects (Liu et al., 2024). An et al. (2014) identified several challenges to coordinated innovation in the region, such as weak innovation foundations, limited cooperation between entities, poor factor flow and sharing, underdeveloped collaborative infrastructure, and insufficient industrial synergy.

Urban function—or urban role—refers to the various production and service activities conducted within a city, encompassing both internal and external functions. External functions define a city's role within a national or regional context, while internal functions cater to the needs and services of its resident population (Jain, M., & Korzhenevych 2019). Research on urban functional specialization has its roots in the study of industrial agglomeration and labor division. Duranton and Puga (2004), examining industrial spatial division in the United States, found that large cities tend to concentrate on services such as R&D and management, whereas small and medium-sized cities focus on manufacturing and processing. Their findings highlighted a shift from sectoral to functional specialization in inter-city divisions of labor. Similarly, Bade et al. (2004) observed that German cities transitioned from sectoral to functional specialization in the internet era, especially within urban agglomerations.

Urban functional optimization results from the combined influence of natural and socio-economic factors. These include resources, ecological conditions, population, technological development, infrastructure, and governance (Yuan et al. 2024; Liu et al. 2022). Helpman (1984) proposed a framework for understanding international labor division based on trade theory, arguing that improvements in information technology and transport enable multinational firms to spatially separate departments across countries. Razin & Hazan (1995) critiqued the limited scope of intra-product division as compared to the broader industrial chain division, which includes production, sales, and R&D processes across multiple sectors. Locay (1990), applying a North-South trade model, suggested that technological progress and the reduction of administrative barriers promote a transition from product-based to function-based labor division within urban agglomerations. Yeung (2009), using a micro-level analysis of MNC location strategies, concluded that China's central cities are increasingly competitive in attracting high-value-added functions, reflecting a trend toward functional specialization. Tavares et al. (2019) emphasized that industrial development drives the enhancement of urban functions, supported by urban upgrading, enabling conditions, and feedback mechanisms that in turn reshape these influences. Fang (2015) further argued that alongside traditional drivers—natural conditions, population, transportation, governance—modern influences such as regional labor division, industrial upgrading, inter-regional industrial transfer, and the digital economy also significantly impact urban function evolution.

The inter-regional flow of innovation talent and funding enhances innovation capacity and improves the efficiency of resource allocation via spatial knowledge and technology spillovers. It also strengthens regional connectivity and helps overcome entrenched disparities in innovation development. As a focal point for China's innovation ecosystem, the BTH region must address its current challenges, including insufficient functional specialization and vague inter-city functional differentiation. Promoting the free flow of innovation factors, clarifying the functional roles of individual cities, fostering industrial collaboration, and enhancing urban functional optimization are critical for supporting regional economic prosperity, improving the quality of urban development in the BTH region, and establishing a well-balanced and complementary regional economic structure.

## 2. Theoretical Analysis

#### 2.1 Economic Effects of Innovation Factor Flow in the BTH Region

#### 2.1.1 Resource Allocation Effect

Innovation factor flows facilitate the optimal allocation of resources. Since different regions possess varied resource endowments and advantages, the movement of innovation factors enables more effective integration of these assets, driving regional economic growth. First, a moderate spatial flow of innovation factors increases their stock in receiving areas, laying a solid foundation for innovation activities and ensuring the efficient allocation of human, financial, and technological resources. Second, such flows stimulate interregional competition in innovation, activating the roles of both factor stock and mobility, thus improving the existing allocation structure. With the continued expansion of the science and technology talent pool and rising R&D investments in the BTH region, the allocation efficiency of innovation resources is gradually improving. However, regional disparities remain evident—Beijing maintains a clear lead, followed by Tianjin, with Hebei trailing behind.

## 2.1.2 Knowledge Spillover Effect

Knowledge spillover refers to the unintentional transfer of knowledge, which arises from its partially excludable and non-rivalrous nature. Innovation factors, as carriers of new knowledge and

technology, enable cross-regional dissemination of innovation through overlapping domains. On one hand, such flows foster knowledge exchange and reduce material, temporal, and risk-related costs. On the other hand, R&D personnel and capital often embody substantial knowledge, accelerating the interregional application and diffusion of innovation. This strengthens interregional linkages in innovation productivity, particularly among neighboring cities, and generates a radiating, driving effect that enhances overall regional innovation performance.

#### 2.2 Evolution Mechanism of Urban Functions in the BTH Region

## 2.2.1 From Labor Division to Urban Agglomeration Division

The spatial differentiation of urban functions emerges from the restructuring and optimization of labor division driven by enhanced transaction efficiency. In the early stages of social development, as transaction conditions improved, the cost of self-sufficiency surpassed that of inter-worker exchange, prompting the emergence of specialized labor. As transaction efficiencies continued to improve, inter-city divisions became clearer, prompting cities to evolve distinct functional roles. In practice, the evolution of functional division within urban agglomerations is also shaped by factor costs, technological advancement, administrative fragmentation, and urban development levels (Yu et al., 2018). Enterprises, based on value-added levels across the industrial chain, tend to locate production in suburban or lower-cost cities (due to cheaper land and labor), while placing high-value functions—such as R&D, marketing, and management—in central cities with abundant talent, capital, and information resources (Kang & Ma, 2021).

## 2.2.2 Mechanisms Driving Urban Functional Specialization

As labor division evolves, cities within an agglomeration exhibit growing disparities in labor productivity, product diversity, and market scale, leading to mature industrial specialization patterns. With advancements in digital infrastructure and transportation, functional division of labor has emerged as a new and complementary mode of specialization, gradually overtaking traditional industrial specialization. The transition from labor-based to function-based urban roles is shaped by several mechanisms: regional division of labor, industrial upgrading and relocation, convergent development, and administrative fragmentation (Li et al., 2024).

As regional integration deepens, cities leverage their comparative advantages to specialize in distinct segments of the industrial value chain, forming complementary functional roles. This inter-city functional complementarity not only accelerates local economic growth but also generates spillover effects across the agglomeration (Yu et al., 2021). As productivity improves and technologies advance, industrial structures in large cities shift toward a "tertiary-secondary-primary" configuration, promoting urban functional transformation. In China, high-tech industries remain concentrated in coastal regions, while resource- and labor-intensive industries migrate to inland areas or even to Southeast Asia. Major cities, equipped with research institutes and universities, attract high-end talent and foster technology-intensive industries through knowledge spillovers. Conversely, receiving cities benefit from production expansion and functional specialization improvements.

The BTH urban agglomeration currently exhibits a pronounced "core-periphery" structure. Compared to the Yangtze River Delta and the Guangdong-Hong Kong-Macao Greater Bay Area, the BTH region lags in achieving optimal resource allocation and inter-city labor division. With its coordinated development now elevated to a national strategic priority, the BTH agglomeration must accelerate functional specialization and redefine the specific roles of its constituent cities.

## 3. Research Design

## 3.1 Model Construction

Given the important influence of geographical factors on innovation factor flow and urban development, this paper constructs a spatial econometric model. Considering that the SDM simultaneously accounts for the spatial interaction of both the dependent and independent variables, this paper prioritizes the SDM. Its expression is:

$$Y_{it} = \alpha_0 + \rho W Y_{it} + X_{it} \beta + W X_t \theta + \varepsilon_{it}$$
 (1)

In Equation (1), Y is the dependent variable, X is the explanatory variable, W is the spatial weight matrix (this paper selects the inverse of the straight-line distance between BTH cities as the

weight), i and t represent region and year respectively,  $\rho$  is the spatial autoregression coefficient,  $\rho WY_{it}$  is the spatial lag term reflecting the spatial interaction effect of the dependent variable in other regions,  $WX_t\theta$  reflects the spatial influence of independent variables from other regions,  $\alpha_0$  is the constant term,  $\beta$  and  $\theta$  are coefficients to be estimated, and  $\epsilon_{it}$  is the error term.

#### 3.2 Variable Description and Data Sources

The sample selected for this paper is panel data for 13 prefecture-level and above cities in the BTH region from 2010 to 2020. The dependent variable is urban function. Drawing on Duranton & Puga (2005) 's measurement method for urban functional specialization level, urban functions are classified into four categories: production function, R&D function, management function, and marketing function. The functional specialization index for the 13 cities is calculated using the following formula:

$$FS_{ij} = (E_{ij}/E_i)/(E_j/E) \tag{2}$$

Here, FS<sub>ij</sub> represents the division level of function j in region i, E<sub>ij</sub> represents the number of employees engaged in function j in region i, E<sub>i</sub> represents the total number of employees in region i, E<sub>j</sub> represents the total number of employees engaged in function j in the BTH region, and E represents the total number of employees in the BTH region. The number of production employees comes from "Mining, Manufacturing, Production and Supply of Electricity, Gas and Water" sectors. R&D employees come from "Scientific Research, Technical Services, and Geological Prospecting" sector. Management employees come from "Real Estate, Leasing, and Business Services" sectors. Marketing employees come from "Wholesale and Retail Trade" sector.

The explanatory variables are the flow scale of R&D personnel and funds in the BTH region, this study constructs modified gravity models for different innovation factors that can depict their flow direction:

#### 3.2.1 Modified Gravity Model for R&D Personnel Flow

$$pf_{ij} = \frac{\ln p_i \times \ln pg dp_j}{d_{ij}^2} \tag{3}$$

$$pf_i = \sum_{j=1}^n pf_{ij} \tag{4}$$

Here,  $pf_{ij}$  represents the flow quantity of R&D personnel from region i to region j,  $p_i$  represents the number of R&D personnel in region i (characterized by the full-time equivalent of R&D personnel),  $pgdp_j$  represents the per capita GDP of region j (representing its economic attractiveness),  $d_{ij}$  represents the distance between the centers of the two locations, and  $pf_i$  represents the total outflow of R&D personnel from region i.

## 3.2.2 Modified Gravity Model for R&D Fund Flow

$$cf_{ij} = \frac{\ln r dk_i \times \ln r dk_j}{d_{ij}^2} \tag{5}$$

$$cf_i = \sum_{j=1}^n cf_{ij} \tag{6}$$

Here,  $cf_{ij}$  represents the flow of R&D capital from region i to region j,  $rdk_i$  represents the R&D capital stock in region i,  $rdk_j$  represents the existing R&D capital stock in region j, and  $cf_i$  represents the total outflow of R&D capital from region i.

Considering the significant heterogeneity among regions and the availability of indicators, the following control variables are introduced for testing the mechanism of innovation personnel flow: wage level (WAGE), government participation (GOV), education level (SCH), public service (HOS), informatization level (INTEL), and infrastructure (ROAD). For testing the mechanism of innovation fund flow, the following control variables are used: regional development level (PGDP), industrial structure (INDU), government participation (GOV), and informatization level (INTEL).

Data primarily come from the China City Statistical Yearbook, China Statistical Yearbook on Science and Technology, and Hebei Statistical Yearbook on Science and Technology. Missing data for some years were supplemented using interpolation. Variable descriptions are shown in Table 1.

Table 1 Variable Definition.	s and Descriptions
------------------------------	--------------------

	Variable	Abbreviation	Measurement Indicator
Dependent Variable	Urban Function	FS	Measured according to Eq. (2)
Personnel	Innovation Personnel	PF	Measured according to Eqs. (3)-(7)
	Innovation Funds	CF	Measured according to Eqs. (3)-(7)
	Wage Level	WAGE	Average wage of employees
	Government Participation	GOV	Proportion of local government fiscal expenditure to regional GDP
Control Variables	Education Level	SCH	Sum of the number of ordinary higher education institutions, secondary schools, primary schools, and secondary vocational schools
	Public Service	HOS	Number of hospital beds
	Informatization Level	INTEL	Number of international internet users
	Infrastructure	ROAD	Passenger traffic volume
	Regional Development Level	PGDP	Per capita regional GDP
	Industrial Structure	INDU	Proportion of tertiary industry added value to GDP

## 4. Empirical Results and Analysis

#### 4.1 Mechanism Test of Innovation Personnel Flow on Urban Function Optimization

From a spatial spillover perspective, the flow of innovation personnel within a given region significantly influences its Production, R&D, and Management functions. According to the direct effect results (Table 2), the coefficients for innovation personnel flow on local Production and R&D functions are significantly positive at the 1% and 5% levels, respectively. This suggests that cross-regional movement of innovation talent within the BTH region more effectively contributes to the optimization of urban Production and R&D functions. This outcome closely reflects the existing functional division pattern in the BTH urban agglomeration, wherein Beijing—the core city—primarily undertakes producer service functions such as scientific R&D, finance, and consulting, while peripheral cities in Hebei focus more heavily on production activities.

According to the indirect effect results, the flow of innovation personnel in a region generates measurable spillover effects on the R&D and Management functions of neighboring areas. Notably, R&D specialization appears to generate agglomeration effects that attract additional innovation personnel. Judging from the coefficients of the explanatory variables, the influence of neighboring regions' innovation personnel flow on a city's R&D function exceeds the direct local effect.

Table 2 Effect Decomposition of BTH Innovation Personnel Flow on Urban Function Optimization

	Direct Effect				Indirect Effect			
Variable	Production	R&D	Management	Marketing	Production	R&D	Management	Marketing
	Function	Function	Function	Function	Function	Function	Function	Function
PF	0.636***	1.064*	-0.478	0.514	0.574	-5.534*	8.078**	-0.457
	(0.166)	(0.618)	(0.601)	(0.337)	(0.717)	(3.050)	(3.072)	(1.145)
WAGE	-0.464**	0.304	-1.025*	0.357	0.681*	-1.990	-3.076*	-0.0543
	(0.153)	(0.563)	(0.527)	(0.317)	(0.399)	(1.539)	(1.708)	(0.637)
GOV	0.252***	-0.154	-0.163	0.204	0.376	-0.375	-0.338	-0.0994
	(0.0677)	(0.242)	(0.219)	(0.147)	(0.230)	(0.864)	(0.884)	(0.372)
SCH	0.289**	0.171**	1.229**	0.0914	0.897**	-2.493**	0.880	-0.201
	(0.111)	(0.394)	(0.376)	(0.222)	(0.337)	(1.165)	(1.287)	(0.493)
HOS	-0.125	1.191**	1.134**	-0.0910	0.821**	0.800	1.246	-0.223
	(0.104)	(0.381)	(0.362)	(0.201)	(0.335)	(1.216)	(1.320)	(0.473)
INTEL	0.0192	0.0306	0.0574	-0.104***	-0.0452	0.266	0.123	-0.199**
	(0.0141)	(0.0509)	(0.0493)	(0.0267)	(0.0517)	(0.194)	(0.205)	(0.0795)
ROAD	$0.0591^*$	-0.392**	-0.175	-0.0281	-0.202*	0.176	0.277	0.703***
	(0.0356)	(0.125)	(0.114)	(0.0764)	(0.105)	(0.391)	(0.401)	(0.177)

t statistics in parentheses

#### 4.2 Mechanism Test of Innovation Fund Flow on Urban Function Optimization

According to the direct effect results, the flow of innovation funds in a region has a significant impact on its own production function (effect value 0.105, significant at 10% level), but no significant impact on R&D, management, and marketing functions (Table 3). A possible reason is that the key tasks of BTH ecological environment collaborative governance in recent years have imposed higher requirements for the transformation, upgrading, and green development of regional production manufacturing. Much R&D funding has been invested in enterprise energy conservation, emission

<sup>\*</sup> p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01

reduction, intensive efficiency, and green intelligent development, also making the production functions undertaken by various cities more specialized.

The results of the indirect effects show that the flow of innovation funds does not significantly affect the urban functions of neighboring regions. A possible reason is the highly uneven distribution of innovation funds within BTH, excessively concentrated in the two megacities of Beijing and Tianjin. This may lead to agglomeration diseconomies such as wasted resource factors, declining profits, and rising production costs. Within a specific region, resource factors have a high degree of similarity, and coupled with the characteristic of inter-regional learning, regions gradually converge by learning from others' practices and experiences. For instance, in recent years, policies strongly supporting strategic emerging industries have led various places to compete in developing high-end manufacturing and new energy industries, resulting in some degree of functional similarity, vicious competition, and overcapacity problems. Within the same urban agglomeration region, similarities in resource development conditions are more pronounced, leading to some convergence in the choice of leading industries and problems like non-prominent urban leading functions.

	Direct Effect			Indirect Effect				
Variable	Production	R&D	Management	Marketing	Production	R&D	Management	Marketing
	Function	Function	Function	Function	Function	Function	Function	Function
CF	0.105*	0.126	0.323	0.178	0.167	0.0832	0.976	0.0132
	(0.0598)	(0.214)	(0.196)	(0.121)	(0.145)	(0.487)	(0.606)	(0.314)
PGDP	-0.166**	-0.313	-0.632**	0.0484	-0.269	-0.764	-1.266	0.919**
	(0.0701)	(0.255)	(0.227)	(0.141)	(0.216)	(0.705)	(0.875)	(0.452)
INDU	0.0267	0.0443***	0.0715	-0.0181	0.0344**	-0.122***	-0.0450	-0.0292
	(0.00325)	(0.0111)	(0.0110)	(0.00655)	(0.0108)	(0.0345)	(0.0435)	(0.0234)
GOV	0.0780	0.833**	-0.0953	0.138	$0.387^{*}$	1.002	0.410	0.578
GOV	(0.0803)	(0.283)	(0.264)	(0.163)	(0.226)	(0.757)	(0.942)	(0.510)
INTEL	-0.0412**	-0.0306	-0.0417	-0.0361	-0.0428	0.388**	-0.112	0.308**
	(0.0179)	(0.0660)	(0.0576)	(0.0372)	(0.0570)	(0.190)	(0.234)	(0.124)

Table 3 Effect Decomposition of BTH Innovation Fund Flow on Urban Function Optimization

## 5. Conclusions

This paper analyzes the scale of innovation personnel and capital flows in 13 prefecture-level and above cities within the BTH region from 2010 to 2020 using a modified gravity model. It assesses the regional pattern of functional division and its driving forces by employing a functional specialization index. A spatial econometric model is then constructed to explore the mechanisms through which innovation factor flows influence urban functional optimization. The key findings are as follows:

First, over the past decade, the scale of innovation talent and capital flows within the BTH region has expanded. Investment in S&T innovation has increased steadily, producing substantial innovation outputs. However, the spatial distribution of innovation factors remains highly uneven, with clear regional agglomeration patterns forming a core-periphery structure.

Second, significant disparities exist in the level of functional specialization across cities in the BTH urban agglomeration. A functional division of labor has emerged in which core cities specialize in R&D and management, while peripheral cities focus on manufacturing. The evolution of urban functions is shaped by multiple mechanisms, including regional division of labor, industrial upgrading and transfer, convergent development, and administrative segmentation.

Third, urban functional optimization is driven by the interplay of various factors. Overall, the free flow of innovation factors has, to some extent, mitigated the uneven spatial distribution of innovation resources, improving factor utilization efficiency. However, persistent administrative barriers, weak intercity policy coordination, and large disparities in informatization, infrastructure, and R&D investment levels have hindered the emergence of an integrated innovation ecosystem characterized by fluid factor mobility, synergistic development, and shared technological progress. As a result, core urban functions remain underdeveloped, and functional differentiation within the BTH urban agglomeration is insufficient.

Fourth, although the BTH urban agglomeration has laid a solid foundation for industrial cooperation, its integrated development remains hampered by stark regional disparities, unclear functional positioning among cities, and a lack of cooperative momentum.

t statistics in parentheses

<sup>\*</sup> p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01

#### Acknowledgments

Graduate Science and Technology Innovation Project of Beijing Wuzi University in 2025 "Research on the Impact of Industrial Chain and Innovation Chain Integration on Regional Economic Growth" (Project No.: BWUYKC-11)

#### References

- [1] Deng, J., Chen, T., & Zhang, Y. (2023). Effect of collaborative innovation on high-quality economic development in beijing—tianjin—hebei urban agglomeration—an empirical analysis based on the spatial durbin model. Mathematics, 11(8), 1909.
- [2] Huang, X., & Liu, J. (2020). Regional economic efficiency and its influencing factors of Beijing-Tianjin-Hebei metropolitans in China based on a heterogeneity stochastic frontier model. Chinese Geographical Science, 30(1), 30-44.
- [3] Liu, X., Zhang, X., Yuan, M., Liu, J., & Zhou, G. (2024). Spatial-temporal differentiation of urban eco-efficiency and its driving factors: A comparison of five major urban agglomerations in China. Plos one, 19(3), e0300419.
- [4] An, X., Deng, H., Chao, L., & Bai, W. (2014). Knowledge management in supporting collaborative innovation community capacity building. Journal of Knowledge Management, 18(3), 574-590.
- [5] Jain, M., & Korzhenevych, A. (2019). Detection of urban system in India: Urban hierarchy revisited. Landscape and Urban Planning, 190, 103588.
- [6] Duranton, G., & Puga, D. (2004). From sectoral to functional urban specialization. Journal of Urban Economics, \*57\*(2), 343–370.
- [7] Bade, F. J., Laaser, C. F., & Soltwedel, R. (2004). Urban specialization in the internet age Empirical findings for Germany (Kiel Working Paper No. 1215). Kiel Institute for the World Economy.
- [8] Yuan, X., Chen, B., He, X., Zhang, G., & Zhou, C. (2024). Spatial Differentiation and Influencing Factors of Tertiary Industry in the Pearl River Delta Urban Agglomeration. Land, 13(2), 172.
- [9] Liu, X., Luo, Y., & Huang, M. (2022). Study on the Spatial Structure and City Form Construction of River Valley-Type Cities in the Context of Artificial Intelligence—A Case Study of Northwest China. Wireless Communications and Mobile Computing, 2022(1), 4202745.
- [10] Helpman, E. (1984). A simple theory of international trade with multinational corporations. Journal of Political Economy, \*92\*(3), 451–471.
- [11] Razin, E., & Hazan, A. (1995). Industrial development and municipal reorganization: conflict, cooperation, and regional effects. Environment and Planning C: Government and Policy, 13(3), 297-314.
- [12] Locay, L. (1990). Economic development and the division of production between households and markets. Journal of Political Economy, 98(5, Part 1), 965-982.
- [13] Yeung, H. W. C. (2009). Transnational corporations, global production networks, and urban and regional development: A geographer's perspective on Multinational enterprises and the global economy. Growth and Change, 40(2), 197-226.
- [14] Tavares, A. O., Monteiro, M., Barros, J. L., & Santos, P. P. (2019). Long-term land-use changes in small/medium-sized cities. Enhancing the general trends and local characteristics. European Planning Studies, 27(7), 1432-1459.
- [15] Fang, C. (2015). Important progress and future direction of studies on China's urban agglomerations. Journal of Geographical Sciences, 25(8), 1003-1024.
- [16] Yu, H., Deng, Y., & Xu, S. (2018). Evolutionary pattern and effect of administrative division adjustment during urbanization of China: Empirical analysis on multiple scales. Chinese Geographical Science, 28(5), 758-772.
- [17] Kang, L., & Ma, L. (2021). Expansion of industrial parks in the Beijing–Tianjin–Hebei urban agglomeration: A spatial analysis. Land, 10(11), 1118.
- [18] Li, R., Yu, B., Wang, Q., Wu, G., & Ma, Z. (2024). Changes in economic network patterns and influencing factors in the urban agglomeration of Guangdong–Hong Kong–Macao Greater Bay Area: A comprehensive study. Buildings, 14(4), 1093.
- [19] Yu, X., Wu, Z., Zheng, H., Li, M., & Tan, T. (2020). How urban agglomeration improve the emission efficiency? A spatial econometric analysis of the Yangtze River Delta urban agglomeration in China. Journal of environmental management, 260, 110061.