International Journal of Industrial Engineering and Engineering Management (IJIEEM), Vol. 7, No. 2, December 2025

e-ISSN: 2685-4090 http://ojs.uajy.ac.id/index.php/IJIEEM

Spatial-temporal Pattern and Influencing Factors of Listed Enterprises in China's Strategic Emerging Industries

Peichao Dai
School of Public Administration, Nanjing University of Finance and Economics, Nanjing, China

Email: peichaodai@nufe.edu.cn

*Corresponding author

ABSTRACT

This study analyzes the structure and spatial distribution of listed companies in China's strategic emerging industries (SEIs) from 2010 to 2021, using a quantitative approach. An industrial diversity index is created to assess provincial structures, and spatial agglomeration is examined through a spatial autocorrelation model. The distribution is visualized with kernel density estimation (KDE), and migration patterns of the gravity center are tracked. The key findings are as follows: (1) Significant regional disparities in SEI development exist, with greater diversity in the Yangtze River Delta (YRD), Beijing-Tianjin-Hebei (BTH), and the Pearl River Delta (PRD) compared to other regions; (2) The distribution shows strong positive spatial autocorrelation, indicating a pronounced agglomeration effect; (3) The spatial center of gravity primarily shifts within Central China; (4) The distribution follows a pattern of decreasing concentration from the eastern coastal areas to the western inland regions, with scattered presence in the central and northeastern regions; (5) Key factors such as economic development (DN values), policy support, R&D investments, passenger turnover, and technology market activity play a significant role in shaping the number of listed companies in each region. This analysis offers valuable insights for policymakers aiming to guide regional industrial development.

DOI: https://doi.org/10.24002/ijieem.v7i2.10561

Keywords: ellipse standard deviation, emerging industries, gravity center, industrial diversity index, kernel density model

Research Type: Research Paper

Article History: Received December 29, 2024; Revised June 1, 2025; Accepted June 26, 2025

How to cite: Dai, P. (2025). Spatial-temporal pattern and influencing factors of listed enterprises in China's strategic emerging industries. *International Journal of Industrial Engineering and Engineering Management, 7*(2), 113-124.

1. INTRODUCTION

In September 2010, China introduced the initiative to accelerate the development of SEIs. These sectors, built upon key technological advances, are expected to lead China's economic growth by promoting knowledge-intensive and technology-driven industries. At the same time, the focus on these industries facilitates the upgrading of the industrial structure, promotes a shift from extensive to intensive economic growth, and strengthens China's competitive edge on the global stage. By 2019, the added value of SEIs contributed 11.5% to China’s GDP, and this figure is projected to exceed 17% by 2025 . In the "14th Five-Year Plan" released last year, the importance of advancing these industries and reinforcing national scientific and technological capabilities was reaffirmed.

Many nations and regions have introduced various policies to foster SEIs, leveraging their industry and technology advantages. For instance, the U.S. State Department outlined a national strategy focusing on the growth of "key and emerging technologies," identifying 20 priority sectors such as advanced computing, AI, biotechnology, semiconductors, and advanced manufacturing. Likewise, the European Union published a report on strengthening the industrial value chain, establishing six forward-looking industries, including advanced materials, aero-engine technologies, AI, biotechnologies, energy technologies, and quantum information science, among others. The development of emerging sectors plays a significant role in enhancing economic, scientific, technological, and sustainable development worldwide. For example, offshore wind energy projects continue to supply clean power across Europe, highlighting the employment potential of emerging industries (Bento and Fontes, 2019). In Spain, the government is promoting technological innovation while advancing marine renewable energy (García et al., 2021). Furthermore, some researchers argue that the rise of robotics and automation is crucial for achieving sustainable development goals (Guenat, 2022). From both environmental and economic perspectives, the increasing adoption of electric vehicles is critical for reducing reliance on fossil fuels in the transport sector (Vrabie, 2022), while also significantly cutting greenhouse gas emissions and fostering sustainable urban development (Isik, 2021).

The development and spatial distribution of emerging industries are influenced by multiple factors, including policies, technological advancements, financial services, and leading enterprises. A key aspect of the commercialization of emerging technologies is the ability of firms to convert innovations into marketable products. From an enterprise efficiency standpoint, market demand largely determines the location of production for emerging industries (Krugman and Venables, 1995). Driven by profit motives, businesses often favor larger markets (Heiens et al., 2019). Additionally, high-tech firms founded by academic entrepreneurs are likely to prioritize proximity to universities, research institutions, and capital markets. (Kolympiris et al., 2015). On one hand, the development of transportation infrastructure lowers communication costs and facilitates the flow of personnel, capital, and other resources (Donaldson and Hornbeck, 2016). A well-connected transport network encourages businesses to concentrate in key cities, reduces market fragmentation, and enhances resource allocation efficiency (Wang et al., 2021). In contrast, rising transaction costs are a significant factor contributing to the uneven distribution of enterprises (Venables, 2000). On the other hand, areas offering ample land supply are particularly attractive to businesses and can greatly influence their spatial distribution (Dai et al., 2021). Furthermore, industrial policies play a crucial role in shaping the location of emerging industries. All else being equal, firms tend to gravitate toward regions with lower tax burdens (Goel and Haruna, 2007).

The operational data of listed firms serve as a key indicator for assessing their scale and growth potential. This paper examines the diversity index of SEIs using data from industrial companies listed on China’s A-share market between 2010 and 2021. Further analysis of the spatial autocorrelation patterns of these companies is conducted using Moran's I index. By applying spatial analysis and statistical techniques, the paper explores the distribution, evolution trends, and factors influencing the location of listed companies in strategic emerging sectors, offering valuable insights for research on the evolution of business clusters.

2. MATERIALS AND METHODS

2.1. Data source

The data for this study are derived from companies in SEIs listed on China’s A-share market from 2010 to 2021. Due to the absence of a specific statistical category for these industries, experts classify them based on the primary business activities of the listed companies. The data sources include the Choice financial platform, China Stock Market & Accounting Research (CSMAR) database, and Wind economic database. Key indicators in this study include stock code, industry name, enterprise address, administrative region code, revenue, and others. Additionally, using the enterprise address, longitude, and latitude coordinates are matched through AutoNavi’s API and then converted to World Geodetic System (WGS84) coordinates. After excluding special treatment (ST) and delisted companies, a total of 1,749 companies in SEIs are selected as research samples.

Data for mechanism analysis primarily comes from official sources, such as local statistical yearbooks. Indicators like the growth rate of R&D investment, passenger turnover, technology market turnover, the number of patents granted in each province, sulfur dioxide emissions, university growth rates, and power consumption growth rates are derived from original data or calculated results from the Statistical Yearbooks. Policy data are sourced from Peking University’s Magic Weapon database, which contains all central and local regulations since 1949. The average DN value is obtained from the original Visible Infrared Imaging Radiometer Suite (VIIRS) satellite data provided by the National Geophysical Data Center (NGDC) of the United States.

Table 1. Types of SEIs

No	Industry Category	Segment Industries
1.	High-end equipment manufacturing industry	Rail transit equipment, marine engineering equipment, aviation equipment, satellites and their applications, and intelligent manufacturing.
2.	Energy conservation and environmental protection industry	Energy-efficient industry, advanced environmental protection industry, and resource recycling industry.
3.	Biological industry	Biological agriculture, biomedical engineering, biomedicine, biological manufacturing, and biomass energy.
4.	Digital creative industry	Digital creative equipment, digital content, and digital design services.
5.	New material industry	High-performance composites, advanced structural materials, and new functional materials.
6.	New energy industry	Wind energy, nuclear power technology, solar energy, and smart grid.
7.	New energy vehicle industry	New energy vehicles.
8.	New generation information technology	Electronic core foundation, high-end software and emerging information services, and next-generation information network.

The industrial structure upgrading index is calculated using the Theil index, while a gray prediction model is applied to fill in missing data for certain years.

Based on China's 13th Five-Year Plan for the Development of National Strategic Emerging Industries, the Decision on Accelerating the Cultivation of Strategic Emerging Industries, the National Economic Industry and Code (GB/T 4754-2017), and the Classification Criteria of High-Tech Industries (2017), SEIs are classified into eight categories (Table 1).

2.2. Method

2.2.1. Industrial diversity index

The industrial diversity index quantifies how evenly revenue is distributed across different strategic emerging industries (SEIs) within a province. A region with only one industry, the diversity index would be 0, indicating no variety. Conversely, a province that hosts multiple industries has a higher index, reflecting balanced revenue contributions. The index uses information entropy, a measure of system "disorder," where higher entropy means more industries coexist with comparable revenue shares. For instance, if a province's SEIs generate equal revenue across all sectors, entropy reaches its maximum value. The information entropy of the strategic emerging industry structure indicates the level of order within provincial industries. A higher entropy value suggests a lower level of order, greater differences in the industrial structure, and a more complex distribution of industries. Conversely, a lower entropy value indicates a higher degree of order in the industrial structure and fewer types of industries (Dong and Li, 2022). The calculation formula is as follows:

$$G_j^i = -\sum_{j=1}^{m} P_j^i \ln P_j^i \tag{1}$$

Here, the diversity index of SEIs. (G_j^i) in province j reflects the industrial structure through information entropy, with units in bits (NAT). P_j^i indicates the proportion of revenue generated by listed companies in SEIs relative to the total revenue of such companies in the province j. This diversity index measures the evenness in the distribution of SEIs across provinces. According to the maximum-minimum entropy principle, when a region contains only one type of industry, entropy is at its minimum, i.e., G_j^i=0. Conversely, when the revenues of industrial listed companies are evenly distributed within a province, the industrial structure is stable, and information entropy reaches its maximum. As the number of strategic emerging industry types increases, the system's order decreases, and entropy rises.

2.2.2. Moran's index

The spatial autocorrelation analysis adopts a contiguity-based spatial weight matrix, which posits that geographically proximate regions exhibit stronger industrial interactions. Sensitivity analyses substituting economic distance weights yielded negligible deviations in global Moran's I values, reinforcing the robustness of spatial dependence patterns. Moran's I evaluates whether regions with similar numbers of SEI firms cluster together geographically. A positive value suggests that provinces with many firms tend to neighbor other high-density provinces, while a negative value would imply a checkerboard-like pattern. The analysis consistently showed positive Moran's I values, confirming that SEIs aggregate in "hotspots" rather than scattering randomly.

Spatial autocorrelation is a primary technique for identifying spatial relationships among geographical elements (Liu et al., 2021). Moran's I index measures the degree of spatial autocorrelation, taking into account both the attribute values of the elements and the spatial distance between them. The formula is as follows (Wang et al., 2020).

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1,j\neq i}^{n} w(i,j)(x_i-\bar{x})(x_j-\bar{x})}{\left[\sum_{i=1}^{n}\sum_{j=1,j\neq i}^{n} w(i,j)\right]\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{2}$$

where $\bar{x} = \sum_{i=1}^{n} x_i/n$, x_i and x_j represent the observed values of a spatial aspect on the regional units. *i*, *j*, and w (i, j) are the spatial weight matrix.

2.2.3. Kernel density estimation

KDE assumes that all listed firms within a given bandwidth contribute equally to local industrial density estimates, regardless of firm size or sector. The model also treats provincial administrative boundaries as permeable to economic activities. KDE assumes that geographical phenomena can occur anywhere in space, but the likelihood of occurrence varies across different spatial locations (Zuo et al., 2021). To visually demonstrate the spatial clustering patterns of listed companies in various industries, KDE is used to analyze the spatial and temporal distribution characteristics of listed companies in SEIs. The formula is as follows. (Yu et al., 2015).

$$\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K\left[\frac{(x-x_i)}{h}\right] \quad (3)$$

Where $\hat{f}(x)$ is the estimated density value at location x, K[ ] is the kernel function, $h > 0$ is the bandwidth, n is equal to the total number of features within the bandwidth, d is the dimension of the data; and $(x - x_i)$ is the distance between feature x_i and location x.

2.2.4. Spatial distribution of the gravity center and migration

The gravity center calculation weights firm locations solely by operating income, reflecting Porter's emphasis on revenue as a proxy for industrial activity concentration. While this assumption excludes employment or asset-based metrics, revenue data's comprehensive coverage in financial databases ensures comparability across provinces.

The spatial barycenter transfer model illustrates the migration path and the trend of both centralized and dispersed distribution of spatial attributes, helping to analyze spatial changes in regional characteristics (Zhang et al., 2018). The movement of the gravity center reflects the asynchronous changes of listed companies in various SEIs across regions. The formula is as follows:

$$X = \left(\sum_{j=1}^{n} x_j E_j\right) / \left(\sum_{j=1}^{n} E_j\right);$$
$$Y = \left(\sum_{j=1}^{n} y_j E_j\right) / \left(\sum_{j=1}^{n} E_j\right) \quad (4)$$

Where E_j is the total operating income of the listed companies in the SEIs of the province j. x_j and y_j are the geometric center coordinates of the provincial administrative unit. X and Y are the coordinates of the spatial distribution of the gravity center of each type of strategic emerging industry.

Gravity center migration model. The calculation formula of the gravity migration distance d_i of SEIs in a region in a year i is as follows:

$$d_i = c \times \sqrt{\left(y_j - y_i\right)^2 + \left(x_j - x_i\right)^2} \quad (5)$$

Where (x_i, y_i) and (x_j, y_j) represent the gravity coordinates of a certain attribute in years i and j, respectively, and c is generally considered a constant (1° ≈ 111 km).

3. RESULTS

3.1. Diversity analysis of SEIs

The results of the industrial diversity index show that from 2010 to 2021, the industrial development of China's provinces varied greatly (Fig. 1). Jiangsu Province, obtained a diversity index of 1.81, the highest of all provinces in 2014, while Xinjiang and Tibet had only one type of industry in 2010, and thus, their diversity indices were 0. On the basis of industrial diversity, the development of SEIs in the YRD, BTH, PRD is relatively balanced, and their average annual diversity indices are all greater than 1, at 1.5, 1.26, and 1.12, respectively. However, the average annual diversity index of Northwest China (Inner Mongolia, Gansu Province, Qinghai Province, Ningxia Hui Autonomous Region, and Xinjiang Uygur Autonomous Region) is less than 1, with Gansu Province having the highest industrial diversity index, 0.84, and Xinjiang having an industrial diversity index of only 0.41. The average annual industrial diversity indices among provinces in Northeast China (Heilongjiang, Jilin, and Liaoning) are significantly different, and the highest index in Jilin Province is 2.01 times that in Heilongjiang Province. The development situations of Southwest China (Yunnan, Guizhou, Sichuan, Chongqing, and Tibet) and Northeast China are similar, and the diversity of industrial development among provinces varies significantly. The highest Sichuan Province is 3.88 times that of the Tibet Autonomous Region. The average annual industrial diversity index of Henan, Hunan, Anhui, and Jiangxi Provinces in the central region has reached 1.47, while the average index value of Shanxi and Hubei Provinces is only 0.65. Thus, the development levels of industrial diversity between these regions are significantly different.

From the time series, it can be seen that from 2010 to 2021, the diversity index of SEIs in the YRD, BTH, and PRD showed a gradual growth trend (Figure 1). However, due to the impact of coronavirus disease 2019 (COVID-19), there was a relatively significant adjustment in 2020. For example, compared with 2019, the industrial diversity index of Guangdong Province in 2020 decreased by 52.36%, that of Zhejiang Province decreased by 43.14%, and that of Beijing decreased by 39.92%. However, over the same period, the provinces in Northwest and Southwest China experienced relatively rapid growth, with the industrial diversity index of Yunnan increasing by 38.24%, that of Tibet increasing by 29.51%, and that of Gansu increasing by 11.35%. From 2020 to 2021, the regions where the diversity index of SEIs fell rapidly in the early stage recovered rapidly. For example, the industrial diversity index of Guangdong Province in 2021 was 2.09 times that in 2020 while that of Zhejiang Province, Beijing, and Shanghai increased by 78.51%, 65.65%, and 37.86%, respectively. However, Shanxi and Xinjiang, where the index was relatively stable in the early stage, fell by 59.53% and 43.12%, respectively.

3.2. Autocorrelation characteristics of spatial patterns

To examine the spatial change trend of the distribution patterns of listed companies in China's SEIs from 2010 to 2021, the number of listed companies in each province is counted, and the global Moran's I index for each province is calculated. Table 2 indicates that the global Moran's I values over the 12-year period are positive and statistically significant, indicating a notable positive spatial autocorrelation in the spatial distribution of listed

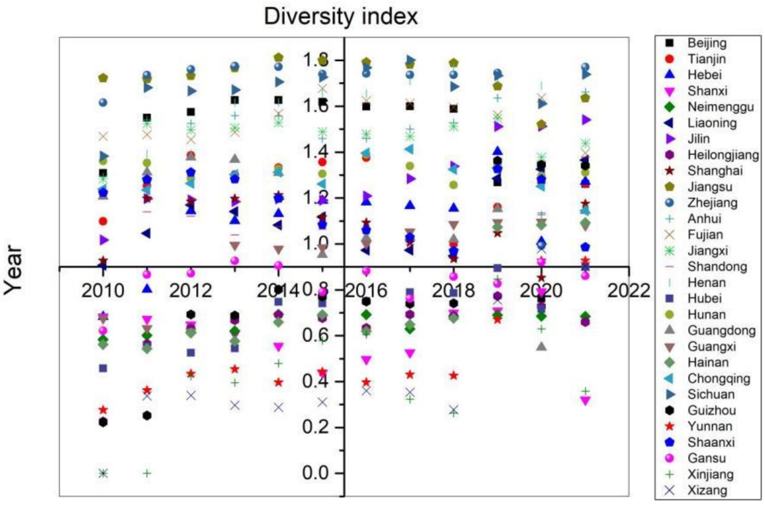

Figure 1. Industrial diversity of listed companies in SEIs in China

Table 2. Spatial correlation of strategic emerging enterprises in China

	Number of listed enterprises	Moran's I	Z	p-value
2010	179	0.117	4.978	0.000
2011	319	0.096	5.742	0.000
2012	403	0.077	5.553	0.000
2013	403	0.077	5.553	0.000
2014	469	0.075	6.002	0.000
2015	571	0.071	6.507	0.000
2016	668	0.077	6.909	0.000
2017	881	0.079	7.463	0.000
2018	929	0.080	7.721	0.000
2019	1073	0.078	7.988	0.000
2020	1383	0.090	10.497	0.000
2021	1749	0.101	13.222	0.000

companies in China's SEIs. In other words, the distribution of listed companies across regions exhibits characteristics of spatial agglomeration.

The spatial agglomeration of SEIs in China reveals a dynamic interplay between policy-driven dispersion and market-led re-concentration, characterized by a U-shaped trajectory in global Moran's I values. Initially, the sharp 34% decline in spatial autocorrelation from 2010 to 2012 reflects the post-financial crisis decentralization, as firms reduced their regional dependency risks. This dispersion phase contrasts with the subsequent stabilization period (2013–2019), where moderate agglomeration persisted despite rising firm counts (Table 2), signaling policy balancing—centralized R&D subsidies in coastal provinces offset dispersion incentives for resource-intensive sectors like energy conservation. Notably, the late re-concentration surge (2019–2021) aligns with China's "Dual Circulation" strategy, accelerating NEV and digital infrastructure investments in eastern clusters.

3.3. KDE of strategic emerging industry enterprises

As shown in Figure 2, the distribution of listed companies in China's SEIs generally decreases from the eastern coastal regions to the western inland areas, with a scattered distribution in the central and northeast regions. The Yangtze River Delta (YRD), Beijing-Tianjin-Hebei (BTH), and Pearl River Delta (PRD) form the dominant high-density clusters, collectively accounting for over 60% of listed SEI firms. These regions exhibit continuous spatial integration, driven by advanced infrastructure, innovation ecosystems, and policy synergies. For instance, the YRD's density hotspot spans Shanghai, Jiangsu, and Zhejiang, reflecting cross provincial industrial linkages in high-end manufacturing and digital creativity. Northwest China, comprising Gansu, Ningxia, Qinghai, and Xinjiang, along with Shanxi and Inner Mongolia in North China, is are area with low density.

Figure 3 illustrates the spatial agglomeration patterns of strategic emerging industries (SEIs) in China. Three prominent geographical features emerge from the kernel density analysis: First, the Yangtze River Delta (YRD), Beijing-Tianjin-Hebei (BTH), and Pearl River Delta (PRD) regions form primary agglomeration cores for most industries. Second, coastal linearity characterizes the distribution of high-tech industries like new energy and biomedicine, extending from northern to southeastern coastal zones. Third, central-western regions exhibit a "multi-node scattering" pattern, with sporadic clusters concentrated along provincial borders.

Sectoral variations reveal that capital-intensive industries (e.g., high-end equipment manufacturing, new materials) predominantly cluster in core economic zones while emerging sectors like new energy vehicles show transitional characteristics with dual concentrations in coastal hubs and selected inland junctions. Environmental industries demonstrate unique spatial duality - intensive coastal clusters coexist with hinterland diffusion along major transportation corridors.

3.4. Analysis of the gravity center distribution of strategic emerging industry enterprises

The rotation angle θ of the standard deviation ellipse indicates a significant variation in the spatial distribution of listed enterprises in China's SEIs, ranging from 11.79° to 170.21°. In 2010, the rotation angle was 26.9°, showing a spatial trend from "northeast to southwest." By 2021, the

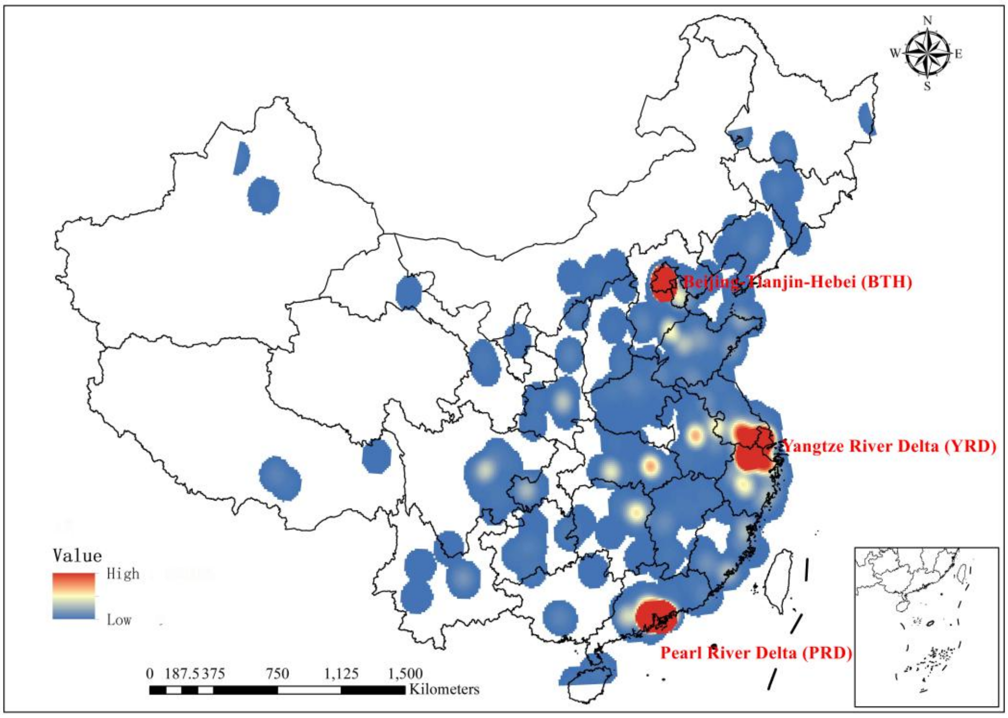

Figure 2. Kernel density of listed companies in China's SEIs

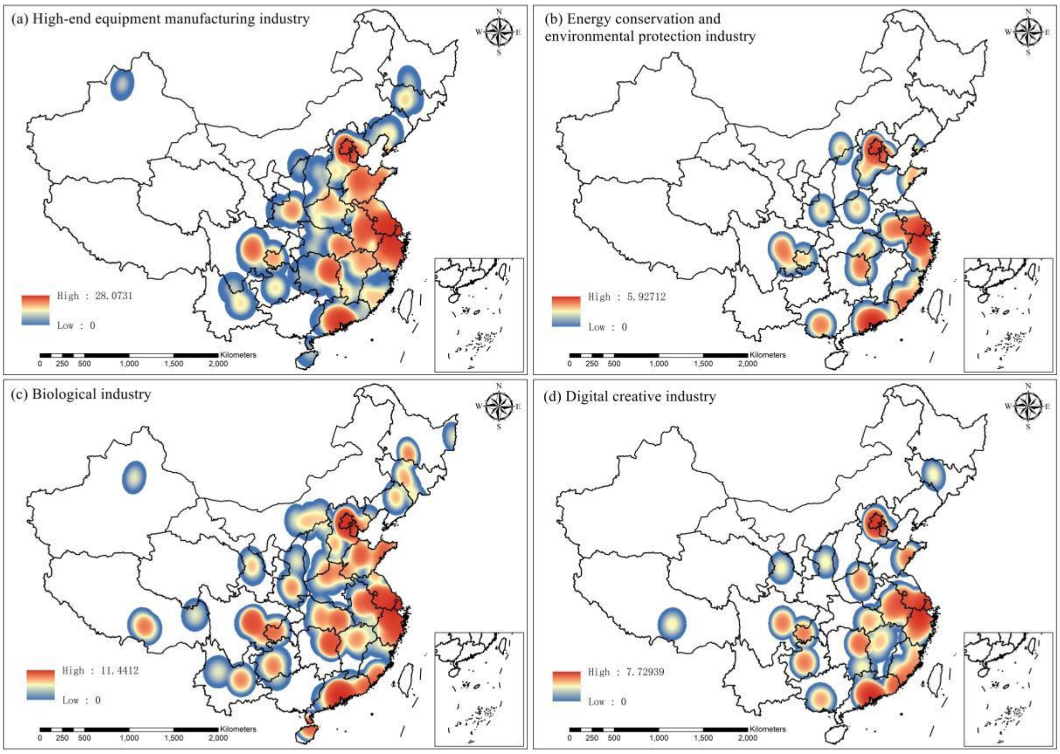

Figure 3. Kernel density of listed companies in different types of SEIs in China

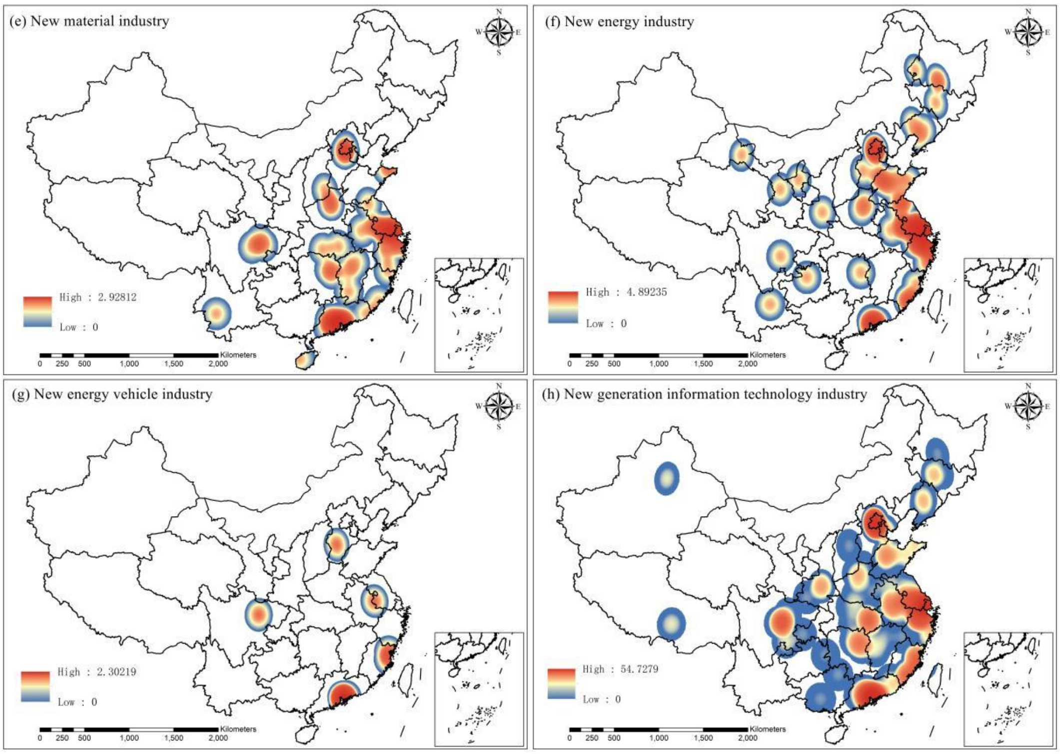

Figure 3. Kernel density of listed companies in different types of SEIs in China (Continued)

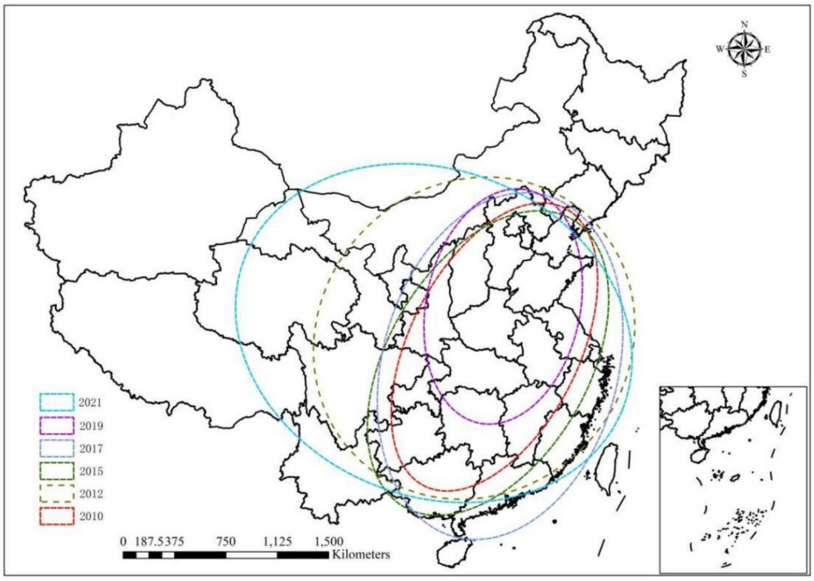

Figure 4. Standard deviation ellipse of listed companies in China’s SEIs

angle reached 112.04°, indicating a "northwest to southeast" spatial trend. Similar trends were observed in 2014, 2017, and 2019, while 2018 showed a distribution resembling a "due east to due west" alignment.

Regarding the coverage of the standard deviation ellipse, the differences from year to year are significant due to the varying lengths of the semi-major and semi-minor axes. In 2010 and 2014, seven to eight provinces were fully covered, with some regions spanning approximately twelve provinces. In contrast, 2011 saw narrower coverage, fully covering only three provinces. In 2012 and 2021, around 54.84% of the provinces were fully covered, while approximately 29.03% were partially covered (Figure 4).

As illustrated in Figure 5, from 2010 to 2021, the spatial position of the gravity center of listed companies in China’s SEIs underwent notable changes. In 2010, the coordinates of the gravity center were 115.7323°E, 29.5920°N while in 2021, they shifted to 116.3673°E, 36.3318°N, resulting in a total migration distance of 751.44 km, indicating a significant shift northward. During most periods, except for the 2014-2015 transition (with a movement of less than 100 km), the gravity center moved more than 100 km. The largest movement occurred between 2018 and 2019, with a shift of 512.64 km. After the China Securities Regulatory Commission suspended IPOs in 2013, the gravity center remained unchanged in 2012 and 2013. Over the 12 years, the center

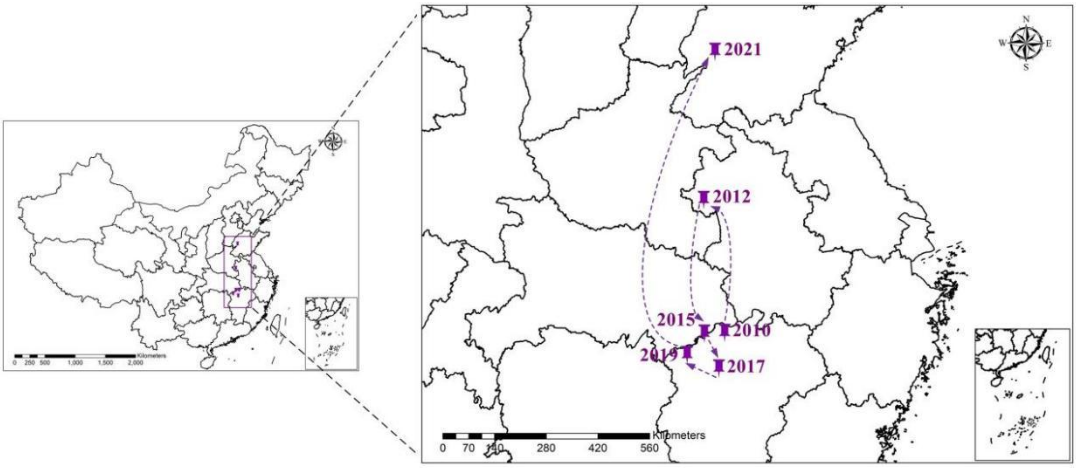

Figure 5. Distribution of the gravity center of listed companies in China's SEIs

Table 3. Test results of the panel model setting form

	Fe	Re	Difference	S.E.
X_1	1.1185680	0.3510970	0.7674712	0.4664911
X_2	6.1294460	0.8213297	5.3081170	1.7362160
X_3	0.3618003	0.3549549	0.0068454	0.1165678
X_4	3.8450730	4.9513840	-1.1063100	0.8349205
X_5	0.2924501	0.0364878	0.2559623	0.1595738
X_6	-3.0677180	2.4665810	-5.5342980	3.4316360
X_7	0.2435131	0.8743021	-0.6307890	0.1592092
X_8	0.9112644	-0.0114461	0.9227106	1.2315850
X_9	0.0650826	0.0451404	0.0199421	0.0151938
X_{10}	0.0027999	0.0036063	-0.0008065	0.0028201

of gravity was primarily located in Jiangxi Province for five years and Hubei Province for three years, suggesting that it was generally centered around China's central region. The movement speed of the gravity center has increased each year since 2015, indicating a broader fluctuation in its spatial distribution.

3.5. Driving factors of the spatial pattern of strategic emerging industry enterprises

The differences in the spatial distribution of listed enterprises in China's SEIs arise from the interaction of multiple factors. Based on existing literature and expert insights, this paper identifies four key explanatory variables for the number of listed enterprises in regional SEIs: economic development, government policy, innovation capacity, and industrial structure. The following variables are selected for empirical analysis: R&D investment (X_1), average DN value (X_2), policy count (X_3), passenger turnover growth rate (X_4), technology market turnover (X_5), advanced industrial structure index (X_6), the number of patents granted in each province (X_7), logarithm of sulfur dioxide emissions (X_8), growth rate of educational institutions (X_9), and electricity consumption growth rate (X_{10}).

The spatial panel model can be applied in two ways: fixed effects and random effects. The choice between these depends on the Hausman test. The statistical outcomes are presented in Table 3. The null hypothesis assumes random effects. With a p-value of 0.0002, which is less than 0.05, the null hypothesis is rejected, leading to the selection of the fixed effects model.

The data is processed using Stata 15.0, and the estimation results are presented in Table 4. From the model parameters, the mean DN value and the number of policies is significant at the 5% level. R&D investment, passenger turnover growth rate, and technology market turnover are significant at the 10% level. All significant variables have positive coefficients, suggesting that these factors contribute positively to the regional distribution of SEIs.

4. DISCUSSIONS

4.1. Spatial pattern differentiation characteristics of listed enterprises in SEIs

The spatial distribution of listed enterprises in strategic emerging industries (SEIs) reveals a pronounced hierarchical structure shaped by China's distinct regional development trajectories. Eastern coastal regions, particularly the Yangtze River Delta (YRD), Beijing-Tianjin-Hebei (BTH), and Pearl River Delta (PRD), emerge as the dominant innovation hubs, accounting for over 70% of high-value-added industries such as advanced equipment manufacturing and new generation

Table 4. Model estimation results

	Coef.	Std.Err.	t	P>|t|	95% Conf.	Interval
X_1	1.118568	0.6383882	1.75	0.090	-0.1851944	2.422331
X_2	6.129446	2.742867	2.23	0.033	0.5277638	11.73113
X_3	0.3618003	0.1336041	2.71	0.011	0.0889444	0.6346562
X_4	3.845073	2.191371	1.75	0.090	-0.6303043	8.320451
X_5	0.2924501	0.1557918	1.88	0.070	-0.0257192	0.6106194
X_6	-3.067718	2.868749	-1.07	0.293	-8.926485	2.79105
X_7	0.2435131	0.2558004	0.95	0.349	-0.2789011	0.7659272
X_8	0.9112644	0.9058586	1.01	0.322	-0.9387456	2.761274
X_9	0.0650826	0.0988995	0.66	0.516	-0.1368972	0.2670623
X_{10}	0.0027999	0.0062631	0.45	0.658	-0.0099912	0.0155909
cons	-14.85719	9.364466	-1.59	0.123	-33.98198	4.267603

information technology. This concentration reflects the synergistic effects of agglomeration economies, where dense R&D networks and knowledge spillovers among firms amplify productivity. In contrast, central provinces like Hubei, Hunan, and Anhui exhibit secondary agglomeration patterns, acting as transitional zones where coastal technologies diffuse inland through supply chain linkages.

SEIs are highly knowledge-intensive, with innovation and technological activities central to their growth. These sectors have high-value-added production, relying heavily on R&D and skilled labor, which results in strong regional clustering. The energy conservation and environmental protection industries, along with new material sectors, are primarily located in economically large regions like Eastern and Central China. The high-end equipment manufacturing and biotechnology industries are spread across the East, Central, Northeast, and Southwest, benefiting from the established industrial base in these areas. The new energy vehicle (NEV) sector is closely tied to government policies and the industrial supply chain. Finally, new-generation information technology and digital creative industries are concentrated in regions with significant industrial capabilities, including software R&D, technology, and universities.

4.2. Driving factors for the distribution of listed enterprises in SEIs

The spatial distribution of SEIs is primarily influenced by market, economic, policy, scientific, and technological factors. Market forces initiate agglomeration by reducing operational costs—enterprises clustering in economic hubs like the Yangtze River Delta gain efficiencies through shared infrastructure, labor market pooling, and proximity to suppliers, which collectively lower transportation expenses compared to dispersed locations. Agglomeration also deepens the social division of labor, develops local industrial chains, and supports the growth of businesses of all sizes across upstream and downstream sectors.

Industrial policies, especially during early industry development, shape the spatial distribution of strategic emerging industry enterprises. Government policies act as the primary scaffolding for SEI distribution, setting the "rules of the game" through fiscal incentives, regulatory frameworks, and spatial planning. Governments offer fiscal and tax incentives to attract businesses, build industrial parks, enhance infrastructure, and improve the business environment. These policies foster industry clusters by creating coordinated systems for fiscal, taxation, finance, land, and intellectual property. A favorable policy environment supports the market's role in resource allocation and promotes the agglomeration of these industries.

Scientific and technological factors also play a role, with universities and research institutes providing crucial talent and technical support. Enterprises benefit from integrating innovative knowledge from various sources, which fosters innovation spillovers, enhances productivity, and facilitates technology diffusion. The collaboration between industry, academia, and research drives R&D activities while a strong higher education population bolsters regional technological capacity, attracting high-level talent (Acevedo-Urquiaga et al., 2021). As a result, enterprises concentrate in areas rich in human capital, where information resources and an innovative culture boost R&D effort and foster industrial clusters centered on technology and innovation.

4.3. Global patterns and institutional variations in strategic industry localization

The spatial agglomeration of strategic emerging industries (SEIs) exhibits distinct global trajectories shaped by industrial heritage, policy frameworks, and institutional capacities. Comparative analysis reveals that while China's SEI clustering predominantly reflects policy-driven spatial reorganization, advanced economies like the US and Japan demonstrate path-dependent agglomeration rooted in legacy industrial ecosystems. For instance, Klier and McMillen (2008) conditional logic analysis of the US automotive corridor demonstrates how transport logistics costs maintain spatial clustering of suppliers even as new entrants emerge. This contrasts with Japan's metropolitan area, where Yamada and Kawakami (2016) identify multilayered growth clusters centered on automobile manufacturing but increasingly supplemented by synergistic service sectors. Their exploratory spatial analysis reveals that while core transportation equipment clusters retain geographical proximity, associated service industries exhibit broader technological clustering through inter-firm knowledge networks (Yamada and Kawakami, 2016).

Emerging economies like Thailand present alternative models of industrial localization. Kuroiwa et al. (2024) employ Duranton and Overman's continuous approach to show that Thai automotive parts suppliers cluster within 150km of assembly plants. The European case reveals contrasting tensions between agglomeration efficiencies and distributive justice. Szabó and Newell (2024) analysis of the EU's just transition in automotive exposes how Germany's core position in global value chains concentrates high-value R&D and battery production while Central/Eastern European states compete for assembly plants. This difference underscores the role of institutional capacity: There is a high level of agglomeration in countries with established automotive industries – the US, UK, Germany, France, Italy, and Japan account for 75 percent of the total contracts (Yeung, 2023).

4.4. Implications on industrial engineering and engineering management

The spatial-temporal patterns factors of China's strategic emerging industries (SEIs) elucidate critical pathways for optimizing industrial ecosystems, particularly in the realms of resource allocation, operational efficiency, and systemic resilience. From an industrial engineering perspective, the pronounced spatial autocorrelation and kernel density clusters validate the efficacy of agglomeration economies, where proximity fosters knowledge spillovers and collaborative innovation. For instance, the "Yangtze River Delta Integrated Circuit Industry Park" exemplifies how spatial clustering reduces transaction costs and accelerates technology diffusion by concentrating upstream suppliers and downstream assemblers within highly diverse regions.

Moreover, the gravity center migration analysis reflects evolving policy priorities and infrastructure investments. This trend underscores the need for dynamic resource allocation strategies. In addressing systemic resilience, the COVID-19-induced volatility in industrial diversity emphasizes the vulnerability of centralized systems. Industrial engineers must adopt multiregional redundancy frameworks, such as replicating critical supply nodes to mitigate risks. Concurrently, investments in intercity transportation and digital networks ensure sustained talent and resource flows during disruptions.

Furthermore, the spatial autocorrelation confirms the self-reinforcing nature of innovation ecosystems. Leveraging this dynamic, engineering managers should colocate R&D centers with academic hubs to capitalize on knowledge spillovers. Institutional frameworks, such as joint patenting and technology market activity, must be scaled to accelerate commercialization. The study's findings advocate for policy-engineering synergies to foster agile industrial systems. The dual focus on innovation diffusion and adaptive policy-making equips stakeholders to navigate the complexities of SEI development in a rapidly evolving global landscape.

4.5. Limitations and prospects

Listed companies offer valuable data for analyzing the structure and spatial distribution of SEIs in China. By using information entropy, a measure of complexity, this study thoroughly examines the industrial structure of strategic emerging sectors across different provinces. Variations in economic development, technological levels, and natural resources lead to differences in both the structure of these industries and the number of listed companies across regions. The spatial agglomeration effect and distribution mapping help illustrate these differences. However, as China's listed companies do not consistently categorize these industries, the sample of companies included in this study was determined by experts based on their primary business. This approach may exclude some relevant companies. Additionally, due to the availability of data at the provincial level, the analysis of driving factors for spatial patterns is limited and could benefit from further refinement.

There are additional data types that could enhance scientific research, such as investigating the distribution patterns of listed companies in various SEIs over time. The Getis-Ord G*i index can help identify hot and cold spots. Furthermore, analyzing county- and district-level socioeconomic data could provide deeper insights into the factors driving spatial pattern changes in these industries across regions.

5. CONCLUSIONS

The spatial distribution of enterprises is a key research focus, and SEIs are crucial for future industrial development. As a significant driver of economic growth, they should be studied from multiple perspectives. This paper uses data from listed companies in China's SEIs to examine the diversity and spatial distribution of these industries through the lens of industrial structure classification. The diversity index highlights regional variations in industry structures across China, revealing distinct industrial development patterns. A spatial analysis model is used to measure the agglomeration of SEIs, based on the coordinates of listed companies. Moran's I index further investigates the spatial distribution and evolution trends of these industries. The KDE method visualizes the aggregation characteristics while the gravity center calculation reflects spatial changes. Finally, the driving factors behind the regional spatial patterns are analyzed.

From 2010 to 2021, the types and spatial distribution of listed companies in China's SEIs exhibit clear characteristics. First, diversity is notably more pronounced in regions like the YRD, BTH, and PRD, compared to the northwest and northeast regions. Second, the spatial distribution generally decreases from the southeast coast to the northwest, with the central and northeast regions showing a more scattered pattern.

Lastly, analysis of the influencing factors reveals that the average value of DN, R&D investment, technology market turnover, and passenger turnover growth all significantly promote the number of listed companies in regional SEIs.

ACKNOWLEDGEMENT

Funding: This research was funded by the Jiangsu Provincial Social Science Application Research Elite Project (24SYC-020), General Project of Philosophy and Social Science Research in Colleges and Universities in Jiangsu Province (2023SJYB0265), and the Nanjing Soft Science Research Program Project (202303014).

REFERENCES

Acevedo-Urquiaga, A.J., Sablón-Cossio, N., Acevedo-Suárez, J.A., & Urquiaga-Rodríguez, A.J. (2021). A Model with a collaborative approach for the operational management of the supply chain. *International Journal of Industrial Engineering and Management*, *12*(1), 49-62.

Bento, N., & Fontes, M. (2019). Emergence of floating offshore wind energy: Technology and industry. *Renewable and Sustainable Energy Reviews*, *99*, 66-82.

Dai, P., Sheng, R., Miao, Z., Chen, Z., & Zhou, Y. (2021). Analysis of spatial–spatial-temporal characteristics of industrial land supply scale in relation to industrial structure in China. *Land*, *10*(11), Article 1272.

Donaldson, D., & Hornbeck, R. (2016). Railroads and American economic growth: A “Market Access” approach. *The Quarterly Journal of Economics*, *131*(2), 799-858.

Dong, L., & Li, X. (2022). Evolution of urban construction land structure based on information entropy and shift-share model: An empirical study on Beijing-Tianjin-Hebei urban agglomeration in China. *Sustainability*, *14*(3), Article 1244.

García, P.Q., Sanabria, J.G., & Ruiz, J.A.C. (2021). Marine renewable energy and maritime spatial planning in Spain: Main challenges and recommendations. *Marine Policy*, *127*, Article 104444.

Goel, R.K., & Haruna, S. (2007). Cooperative and noncooperative R&D with spillovers: The case of labor-managed firms. *Economic Systems*, *31*(4), 423-440.

Guenat, S., Purnell, P., Davies, Z. G., Nawrath, M., Stringer, L. C., Babu, G. R., ... & Dallimer, M. (2022). Meeting sustainable development goals via robotics and autonomous systems. *Nature Communications*, *13*, Article 3559.

Heiens, R.A., Pleshko, L.P., & Ahmed, A.A.A. (2019). Comparison of the relationship marketing outcomes of SMEs vs large enterprises in the Kuwait fast food industry. *British Food Journal*, *121*(10), 2442-2453.

Isik, M., Dodder, R., & Kaplan, P.O. (2021). Transportation emissions scenarios for New York City under different carbon intensities of electricity and electric vehicle adoption rates. *Nature Energy*, *6*, 92-104.

Klier, T., & McMillen, D.P. (2008). Evolving agglomeration in the US auto supplier industry. *Journal of Regional Science*, *48*(1), 245-267.

Kolympiris, C., Kalaitzandonakes, N., & Miller, D. (2015). Location choice of academic entrepreneurs: Evidence from the US biotechnology industry. *Journal of Business Venturing*, *30*(2), 227-254.

Krugman, P., & Venables, A.J. (1995). Globalization and the inequality of nations. *The Quarterly Journal of Economics*, *110*(4), 857-880.

Kuroiwa, I., Techakanont, K., & Keola, S. (2024). Evolution of production networks and the localisation of firms: Evidence from the Thai automotive industry. *Journal of the Asia Pacific Economy*, *29*(1), 260-281.

Liu, S., Liu, Y., Zhang, R., Cao, Y., Li, M., Zikirya, B., & Zhou, C. (2021). Heterogeneity of spatial distribution and factors influencing unattended locker points in Guangzhou, china: The case of hive box. *ISPRS International Journal of Geo-Information*, *10*(6), Article 409.

Szabó, J., & Newell, P. (2024). Driving towards a just transition? The case of the European car industry. *Energy Research & Social Science*, *115*, Article 103649.

Venables, A.J. (2000). Cities and trade: External trade and internal geography in developing economies. *World Development*. In Yusuf, S., Wu, W., & Evenett, S.J. (Eds.). (2000). *Local dynamics in an era of globalization: 21st century catalysts for development*, 58-64. World Bank Publications.

Vrabie, C. (2022). Electric vehicles optimism versus the energy market reality. *Sustainability*, *14*(9), Article 5388.

Wang, S., Liu, H., Pu, H., & Yang, H. (2020). Spatial disparity and hierarchical cluster analysis of final energy consumption in China. *Energy*, *197*, Article 117195.

Wang, T., Zhang, Y., Li, Y., Fu, X., & Li, M. (2021). Sustainable development of transportation network companies: From the perspective of satisfaction across passengers with different travel distances. *Research in Transportation Business & Management*, *41*, Article 100687.

Yamada, E., & Kawakami, T. (2016). Distribution of industrial growth in Nagoya metropolitan area, Japan: An exploratory analysis using geographical and technological proximities. *Regional Studies*, *50*(11), 1876-1888.

Yeung, G. (2023). Codifiability and geographical proximity of supply networks in automotive industry. *Erdkunde*, *77*(2), 91-112.

Yu, W., Ai, T., & Shao, S. (2015). The analysis and delimitation of central business district using network kernel density estimation. *Journal of Transport Geography*, *45*, 32-47.

Zhang, G., Zhang, N., & Liao, W. (2018). How do population and land urbanization affect CO_2 emissions under gravity center change? A spatial econometric analysis. *Journal of Cleaner Production*, *202*, 510-523.

Zuo, Y., Chen, H., Pan, J., Si, Y., Law, R., & Zhang, M. (2021). Spatial distribution pattern and influencing factors of sports tourism resources in China. *ISPRS International Journal of Geo-Information*, *10*(7), Article 428.