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Study on the Spatial Correlation between Artificial Intelligence Patent Growth and Regional Innovation Capabilities Based on the Spatial Durbin Model and Geographically Weighted Regression Model

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Abstract. This study aims to deeply analyze the complex spatial linkage mechanism between the growth of artificial intelligence patents in China and regional innovation capacity. Based on panel data from Chinese provinces and municipalities from 2019 to 2023, this research comprehensively employs two spatial econometric methods: the Spatial Durbin Model (SDM) and the Geographically Weighted Regression Model (GWR). The study first reveals significant spatial dependence in regional innovation factors through the Moran's I index. Subsequently, SDM results demonstrate that R&D investment exerts a significant positive direct effect on local patent output, yet its spatial spillover effects exhibit substantial fluctuations—shifting from a negative "siphon effect" in 2019 to positive spillovers in subsequent years, reflecting dynamic changes in interregional competition and cooperation. GWR model analysis further confirms that the impact of university and scientific personnel concentration on R&D intensity exhibits significant spatial heterogeneity, highlighting uneven regional innovation capacity development. The ultimate objective is to provide theoretical support and decision-making basis for governments to formulate scientifically sound regional innovation policies and optimize artificial intelligence industry distribution.

Keywords: AI Patents; Regional Innovation Capacity; Spatial Econometric Models.

1. Introduction

Against the backdrop of intensifying global technological competition, artificial intelligence (AI) stands as a pivotal driver of the new wave of technological revolution and industrial transformation, its strategic importance undeniable. Nations worldwide have elevated AI to a national strategic level, actively positioning themselves to seize technological advantages. With the rapid advancement of AI technology, China has witnessed sustained and rapid growth in related patent numbers, particularly in fields like deep learning, which exhibit exceptionally high compound annual growth rates. Regional innovation capacity serves as a core element driving local economic development, and innovation activities exhibit significant spatial correlation. Innovation within a region not only propels its own growth but also radiates and stimulates surrounding areas[1-2]. However, China faces several contradictions in the growth of AI patents and the development of regional innovation capacity: despite being the world's largest filer of AI patents, patent distribution primarily concentrates on the application layer domestically, with significant vulnerabilities in core technologies. More critically, substantial disparities exist in AI patent volumes and regional innovation capabilities across different areas. Economically advanced regions dominate due to resource advantages, while less developed regions lag behind. This regional imbalance hinders overall innovation advancement. Against this backdrop, exploring the spatial correlation between AI patent growth and regional innovation capacity becomes paramount. Spatial econometric methods enable precise analysis of their complex relationship, revealing distinctive patterns and interactions across regions. Therefore, this study employs Spatial Durbin Models (SDM) and Geographically Weighted Regression (GWR) based on panel data from China's provinces and municipalities between 2019 and 2023[3-4]. It aims to systematically examine the spatial linkage mechanisms and dynamic evolution characteristics between AI patent growth and regional innovation capacity. Specifically, this paper first employs the Moran's I index to test the spatial dependency of innovation factors.

Subsequently, an SDM is constructed to examine the direct effects and spatial spillover effects of R&D investment on patent output. Finally, GWR is utilized to capture the local spatial heterogeneity of how university and scientific personnel agglomerations influence R&D investment [5-6]. This approach aims to provide robust support for governments in formulating scientifically sound regional innovation policies.

2. Model Construction

2.1. R&D Input Generally Promotes Patent Output — Spatial Durbin Model

2.1.1. Experimental Process and Results

Based on the statistical yearbooks released by the National Intellectual Property Administration (2019–2023) regarding domestic invention patent applications in the field of science and technology, and the national R&D input data published by the National Bureau of Statistics (2019–2023), the dataset is extremely large, with particularly prominent data points in Beijing, Shanghai, Jiangsu, and Zhejiang. These outliers cause a high degree of multicollinearity among independent variables, thereby interfering with the calculation of global indicators. Therefore, when applying the Spatial Durbin Model, this study excluded data from Beijing, Shanghai, Jiangsu, and Zhejiang to ensure the model operates normally and outputs accurate values. The details are shown in the table below:

Table 1. Errors Caused by Abnormal Outliers

Parameter Name	Parameter Meaning	Estimated Value
rho (Spatial Autocorrelation Coefficient)	Measures the spatial dependence of observed values across regional units	1.0872
beta (Independent Variable Coefficient)	Reflects the direct impact of independent variables on the dependent variable	270.5388, 7.6408
gamma (Spatial Lag Coefficient of Independent Variables)	Represents the impact of the spatial lag effect of independent variables on the dependent variable	0, -7.6213

As shown in the table 1, when 2019 R&D expenditure (unit: 100 million yuan) and patent data (unit: item) were used as the independent variable and dependent variable respectively, the input of relevant data into the model yielded results that were highly inconsistent with the range of $\rho \in (-1, 1)$ specified by the Durbin Model. Analysis indicates that this inconsistency arises from extremely prominent data in Beijing, Shanghai, Jiangsu, and Zhejiang, which act as abnormal outliers and disrupt the calculation of global indicators. To address this, the model was optimized by applying a logarithmic transformation to the dependent variable based on the original formula:

$$y = \log\left(_{\text{patent\_count\_clean}} + 1\right) \quad (1)$$

Thus, the new 2019 data indicators were obtained as table 2:

Table 2. 2019 Indicators

Variable	Coefficient
Spatial Autocorrelation Coefficient (rho)	0.4386
Direct Effect of R&D Expenditure (beta)	0.9883
Spatial Lag Effect of R&D Expenditure (gamma)	-0.7747

Interpretation of Key Indicators:

Spatial Autocorrelation Coefficient (rho): With a value of 0.4386, it indicates a significant positive spatial autocorrelation. This means that the spatial units under study are not independent of each other; the relevant variables (e.g., dependent variables) of a region are influenced by its neighboring regions, and this influence is positively correlated. Specifically, when the values of relevant variables in neighboring regions are high, the values in the local region also tend to be high [7-8].

Direct Effect of R&D Expenditure (beta): The coefficient is 0.9883, indicating that after controlling for spatial factors, each unit increase in local R&D expenditure has a significant positive promoting effect on local relevant outputs (e.g., innovation performance, depending on the dependent variable in the model), with a promotion effect close to a 1:1 relationship. This reflects a strong direct impact of R&D expenditure on the local region.

Spatial Lag Effect of R&D Expenditure (gamma): The coefficient is -0.7747, implying that R&D expenditure in neighboring regions has a negative indirect impact on the relevant outputs of the local region. A possible reason is that increased R&D expenditure in neighboring regions attracts more innovation resources (e.g., talent, capital) to flow toward them, creating a "siphon effect" that inhibits the development of the local region. Alternatively, competitive relationships may exist, where neighboring regions capture market share in innovation outputs, leading to negative impacts on the local region.

On this basis, the 2020–2023 data were carefully cleaned to exclude abnormal detected values and maintain the robustness of numerical analysis. The Spatial Durbin Model values for 2020–2023 are shown in the table 3:

Table 3. 2020 Indicators

Item	Estimated Value
Intercept Term	-0.0149
Direct Effect of R&D	0.7497
Spatial Spillover Effect of R&D	0.6280
Spatial Autocorrelation Coefficient (rho)	-0.7718
Total Effect	1.3776

Based on the numerical analysis of the table above, the following conclusions are drawn:

Spatial Autocorrelation Coefficient (rho): With a value of -0.7718, it indicates a strong negative correlation in patent output among geographically adjacent regions. This differs from the general expectation of positive correlation due to similarities in economy and technology among neighboring regions. The negative correlation may result from competitive relationships between regions, leading to a seesaw pattern in patent output among adjacent areas; alternatively, specific geographical, economic, or policy factors may inhibit mutual innovation activities between neighboring regions[9-10].

Direct Effect of R&D: The estimated value is 0.7497, indicating that under otherwise unchanged conditions, each 1-standard-deviation increase in local R&D input leads to a 0.7497-standard-deviation increase in patent output. This reflects a significant direct promoting effect of R&D input on local patent output, demonstrating that increasing local R&D input effectively drives the generation of local innovation outcomes and highlights the direct contribution of R&D input to technological innovation.

Spatial Spillover Effect of R&D: The value is 0.6280, meaning that R&D input in one region exerts a positive spillover impact on the patent output of its neighboring regions. Specifically, when a region increases R&D input, it not only boosts its own patent output but also drives a 0.6280-standard-deviation increase in neighboring regions' patent output through technology diffusion and knowledge dissemination, reflecting the interdependence and externality of innovation activities across regions.

Total Effect: The total effect is 1.3776, which is the sum of the direct effect and spatial spillover effect. It represents the comprehensive impact of R&D input on patent output. This value indicates that R&D input has a significant promoting effect on patent output overall, with both the direct local effect and the indirect spillover effect on neighboring regions jointly driving the increase in patent output, underscoring the importance and positive role of R&D input in the regional innovation system.

Table 4. 2021 Indicators

Item	Estimated Value
Intercept Term	-0.0016
Direct Effect of R&D	0.9760
Spatial Spillover Effect of R&D	0.2595
Spatial Autocorrelation Coefficient (rho)	-0.4229
Total Effect	1.2354

Analysis of the values in the table 4 yields the following conclusions:

Spatial Autocorrelation Coefficient (rho): The spatial autocorrelation coefficient is -0.4229, indicating a negative correlation in patent output among geographically adjacent regions. Under normal circumstances, adjacent regions may exhibit similarities in economy and technology, leading to the expectation of positive correlation. However, the negative correlation observed here suggests potential competitive relationships between adjacent regions, or the presence of specific geographical and economic factors that result in opposite trends (rather than concurrent increases or decreases) in patent output among neighboring regions.

Direct Effect of R&D: The estimated direct effect of R&D is 0.9760, meaning that with other conditions held constant, each 1-standard-deviation increase in a region's R&D input leads to a 0.9760-standard-deviation increase in the region's patent output. This indicates a significant positive promoting effect of R&D input on local patent output, with a relatively large impact magnitude, demonstrating that increasing local R&D input is highly effective in enhancing local innovation output (measured by patents).

Spatial Spillover Effect of R&D: The spatial spillover effect of R&D is 0.2595, indicating that R&D input in one region not only promotes local patent output but also exerts a positive spillover impact on the patent output of neighboring regions. Specifically, when a region increases R&D input, neighboring regions experience an increase in patent output due to technology diffusion and knowledge exchange, although the spillover effect is relatively smaller than the direct effect.

Total Effect: The total effect is 1.2354, which is the sum of the direct effect and spatial spillover effect of R&D. It reflects the comprehensive impact of R&D input on patent output, indicating that R&D input has a significant positive driving effect on patent output overall. Both the direct input effect on the local region and the indirect spillover effect on neighboring regions jointly promote the increase in patent output, highlighting the important role of R&D input in regional innovation.

Table 5. 2022 Indicators

Parameter	Estimated Value
Intercept Term	0.0206
Direct Effect of R&D	0.7397
Spatial Spillover Effect of R&D	0.5757
Spatial Autocorrelation Coefficient (rho)	-0.9981
Total Effect of R&D	1.3154

2022 Indicators are shown in table 5. Spatial Autocorrelation Coefficient (rho): The spatial autocorrelation coefficient is -0.9981, a negative value with an absolute value very close to 1. Generally, the spatial autocorrelation coefficient ranges from -1 to 1. A positive coefficient indicates that similar observed values tend to cluster spatially, while a negative coefficient indicates that dissimilar observed values tend to cluster spatially. This result suggests intense innovation competition among neighboring regions, and long-term negative dependence may lead to "innovation desertification."

Direct Effect of R&D: The coefficient for the direct effect of R&D is 0.7397, indicating that each 1-standard-deviation increase in R&D input leads to a 0.7397-standard-deviation increase in patents. This demonstrates that without considering the influence of other regions, local R&D input has a significant positive promoting effect on local patent output. The relatively large coefficient value indicates that R&D input has a notable impact on patent output within the region, and increasing R&D input is of great significance for enhancing the number of patents in the local region.

Spatial Spillover Effect of R&D: The coefficient for the spatial spillover effect of R&D is 0.5757, meaning that R&D input in one region not only affects its own patent output but also generates a positive spillover effect on the patent output of other regions. Specifically, when a region increases R&D input, the patent output of neighboring regions also increases accordingly, indicating the existence of spatial correlation in R&D and patent output among regions, as well as the diffusion and dissemination of knowledge and technology.

Total Effect: The total effect is 1.3154, which is the sum of the direct effect and spatial spillover effect (0.7397 + 0.5757 = 1.3154). The total effect reflects the comprehensive impact of R&D input on patent output, including both the direct impact on the local region and the spillover impact on other regions. Numerically, the comprehensive promoting effect of R&D input on patent output is significant. Both the direct promotion of local patent output and the spatial spillover-driven increase in other regions' patent output indicate that R&D input plays a positive and important role in patent output overall. 2023 Indicators are shown in table 6.

Table 6. 2023 Indicators

Parameter	Estimated Value
Intercept Term	0.0073
Direct Effect of R&D	0.9875
Spatial Spillover Effect of R&D	0.0330
Spatial Autocorrelation Coefficient (rho)	-0.2121
Total Effect of R&D	1.0206

Spatial Autocorrelation Coefficient (rho): The spatial autocorrelation coefficient is -0.2121, which remains negative but has an absolute value significantly smaller than the 2022 value of -0.9981. This indicates that the negative correlation in spatial terms weakened in 2023, meaning the inverse relationship between a region's patent output and that of its neighboring regions was no longer as strong as in 2022. This may be due to the increasingly diversified development of various regions or the growing complexity of factors influencing patent output, making spatial interdependencies less extreme.

Direct Effect of R&D: The coefficient for the direct effect of R&D is 0.9875, meaning that each 1-standard-deviation increase in R&D input leads to a 0.9875-standard-deviation increase in patents. Compared to the 2022 value of 0.7397, this coefficient increased significantly, indicating that in 2023, the promoting effect of local R&D input on local patent output was notably enhanced. This may reflect improvements in the local scientific research system and innovation environment during this year, enabling R&D input to be more effectively converted into patent outcomes.

Spatial Spillover Effect of R&D: The coefficient for the spatial spillover effect of R&D is 0.0330, a substantial decrease compared to the 2022 value of 0.5757. This indicates that in 2023, the positive spillover effect of R&D input in one region on the patent output of other regions weakened significantly. Possible reasons include reduced technological exchange and cooperation between regions, or increased emphasis on technological confidentiality by various regions, leading to a decline in the spatial diffusion effect of knowledge and technology.

Total Effect: The total effect is 1.0206 (0.9875 + 0.0330 = 1.0206), which is the sum of the direct effect and spatial spillover effect. Compared to the 2022 total effect of 1.3154, there was a decrease, primarily driven by the sharp reduction in the spatial spillover effect. Nevertheless, the total effect remains positive, indicating that R&D input still had an overall promoting effect on patent output, although the comprehensive effect in 2023 was relatively weaker than in 2022.

2.1.2. Experimental Conclusions

From the numerical analysis of 2019–2023 data, there is a positive correlation between the growth of artificial intelligence patents and regional innovation capabilities:

In 2019, local governments increased investment in basic research, introduced policies to enhance financial support for basic research, and guided enterprises and social capital to participate, promoting the sound growth of regional innovation capabilities.

In 2020, affected by the epidemic, various regions launched technological innovations for epidemic prevention and control and strengthened collaborative regional innovation development. For example, innovation cooperation in regions such as the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta regions promoted the sharing and optimal allocation of innovation resources.

2021 marked the first year of the "14th Five-Year Plan." Various regions formulated regional innovation development plans in accordance with the plan, and actively promoted green innovation development under the new "green" development concept. For instance, Jiangsu Province provided financial subsidies and tax incentives to green innovation enterprises to drive the green transformation of industries.

Duan Yu [3] pointed out that intellectual property protection has a significant positive impact on regional innovation levels, indicating that protecting the interests of innovation entities is essential to effectively stimulate their subjective initiative for innovation. However, the level of intellectual property protection in most regions remains low. Meanwhile, the state improved relevant intellectual property laws and regulations, cracked down heavily on infringement, protected the intellectual property rights of innovative talents, and greatly promoted regional innovation capabilities. Summary of 2019–2023 is shown in table 7.

Table 7. Summary of 2019–2023 Data

Year	Spatial Autocorrelation Coefficient (rho)	Direct Effect of R&D Expenditure (beta)	Spatial Spillover Effect of R&D Expenditure	Total Effect
2019	0.4386	0.9883	-0.7747	-
2020	-0.7718	0.7497	0.6280	1.3776
2021	-0.4229	0.9760	0.2595	1.2354
2022	-0.9981	0.7397	0.5757	1.3154
2023	-0.2121	0.9875	0.0330	1.0206

Based on the five-year data trends, the following conclusions are drawn:

Spatial Autocorrelation: Positive spatial autocorrelation was observed in 2019, indicating similarities in patent output among regions; negative spatial autocorrelation was observed in subsequent years, suggesting that differences in patent output among regions gradually became prominent, potentially reflecting competitive dynamics.

Direct Effect of R&D Expenditure: Values fluctuated but were mostly close to 1, indicating that R&D expenditure had a significant positive direct promoting effect on local patent output.

Spatial Spillover Effect of R&D Expenditure: Negative in 2019, then turning positive with significant fluctuations in subsequent years, indicating that the impact of R&D expenditure in neighboring regions on local patent output was unstable, with occasional promotion and occasional weakness.

Total Effect: The total effect showed a fluctuating downward trend from 2020 to 2023, indicating that the comprehensive driving effect of R&D expenditure on patent output was weakening.

3. Dense Distribution of Universities and Scientific and Technological Personnel Positively Correlates with R&D Input — Spatial Geographically Weighted Regression Model

3.1. Experimental Process and Results

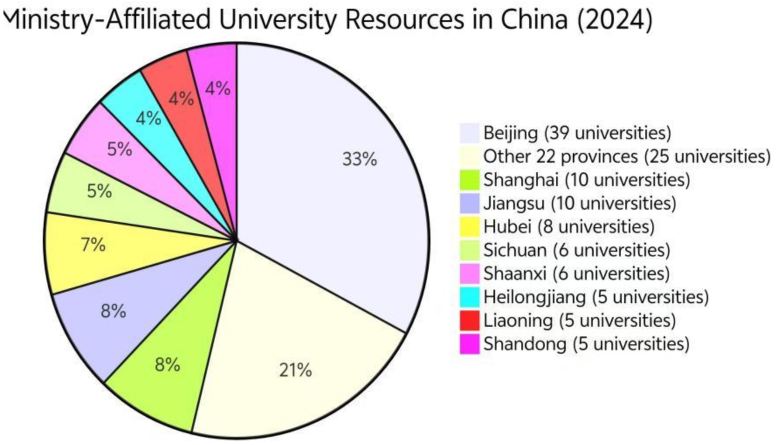

Figure 1. Distribution of Universities

Distribution of Universities is shown in figure 1.In 1998, the State Council issued the Implementation Opinions on Adjusting the Management System of Schools Affiliated to Ministries and Commissions, reforming the university management system. Universities with strong strength and distinctive disciplinary features were placed under the direct management of the Ministry of Education. During this process, some universities originally located in Beijing retained their status as ministry-affiliated institutions, while other regions failed to add many ministry-affiliated universities due to weak university foundations.

Analysis of the data in the table shows that as the national capital and a national political and cultural center, Beijing enjoys policy preferences for concentrating high-quality educational resources, with inherent advantages in disciplinary layout, scientific research investment, and talent aggregation. Regions such as Shanghai, Jiangsu, and Zhejiang have developed local economies, profound cultural heritage, and long-term emphasis on basic education. Additionally, local governments have actively supported university development through preferential policies, thereby attracting more outstanding scientific and technological personnel and resources.

In constructing this model, the concentration of highly educated individuals and scientific and technological personnel was used as the independent variable X, and R&D investment was used as the dependent variable Y.

3.2. Experimental Conclusions

a. Impact of Higher Education on R&D Investment Intensity

Significant Regional Differences: From the series of charts, the coefficient values representing the impact of higher education on R&D investment intensity vary significantly across regions with different longitudes and latitudes. In some regions (e.g., areas with yellowish colors), the coefficient values are relatively high, indicating that higher education has a significant positive promoting effect on R&D investment intensity; in contrast, areas with bluish-purple colors show a weak promoting effect or even a potential negative impact.

Geographical Distribution Characteristics: No obvious single geographical distribution pattern was observed (e.g., simple east-to-west or south-to-north variation). This may be comprehensively influenced by factors such as regional economic development levels, industrial structures, and policy orientations. For example, in economically developed regions that value technological innovation, higher education resources can be better transformed into drivers of R&D investment; in regions with a single industrial structure and low dependence on technology, the role of higher education in promoting R&D investment is limited.

b. Impact of Scientific and Technological Personnel on R&D Investment Intensity

Uneven Impact Magnitude: The coefficient values representing the impact of scientific and technological personnel on R&D investment intensity fluctuate significantly across regions. In areas with yellowish colors, the coefficient values are high, indicating that scientific and technological personnel play a strong driving role in R&D investment intensity in these regions; in areas with bluish-purple colors, the driving role is weak.

Effectiveness of the Geographically Weighted Model: The model confirms that the impact of higher education and scientific and technological personnel on R&D investment intensity is spatially heterogeneous, and the geographically weighted model can effectively capture such regional heterogeneity.

Policy Implications

When formulating R&D investment policies, local governments should adopt region-specific strategies:

In regions with abundant higher education resources, improve the industry-university-research transformation mechanism to unlock the potential of higher education in promoting R&D investment.

In regions with dense scientific and technological personnel, optimize the innovation environment to enhance talent retention and leverage the leading role of scientific and technological personnel.

In regions where both factors are weak, strengthen talent introduction and cultivation, improve the quality of higher education, and gradually enhance R&D investment intensity.

3.3. R&D Input Positively Drives Enterprise Patent Quantity — Moran's I

Based on data from the Statistical Yearbook of Patent R&D by Province (2019–2023) released by the National Intellectual Property Administration, this study adopted the same data processing method as the two aforementioned models, excluding abnormal outliers to ensure the rationality and reliability of the data used for model operation.

The Yangtze River Delta (Shanghai, Jiangsu), Pearl River Delta (Guangdong), and Beijing-Tianjin-Hebei (Beijing, Tianjin) regions have consistently been patent-intensive areas, while western provinces (e.g., Tibet, Qinghai) and some central regions (e.g., Guizhou, Yunnan) have generally had low patent quantities, showing significant east-west disparities. Additionally, the following phenomena were observed:

Radiation Effect of Core Cities: The high patent values of core cities such as Shanghai, Beijing, and Shenzhen show a "core-periphery" diffusion pattern, but the radiation range is limited.

Emerging Hotspot Regions: The standardized patent values of the Sichuan-Chongqing region (Chongqing, Sichuan) increased to 2.5–4.5 in 2022, indicating the rise of a western innovation pole.

Enterprise patents are spatially unevenly distributed, with significant regional differences: economically developed regions have relatively more patents, while economically underdeveloped regions have relatively fewer patents.

In most cases, the spatial distribution of enterprise patents shows a negative correlation, with no obvious spatial agglomeration and significant differences in patent development levels between regions; only in individual cases does a weak positive correlation agglomeration trend emerge. This suggests challenges in promoting collaborative regional innovation development, highlighting the need to strengthen inter-regional technological exchange and cooperation to enhance overall innovation levels and narrow the gap in patent output between regions.

4. Conclusions

This study successfully reveals the complex spatial relationship between AI patent growth and regional innovation capacity using the Spatial Durbin Model and Geographically Weighted Regression. Findings confirm that AI patent growth and regional innovation capacity exhibit an overall positive correlation, with innovation factors demonstrating significant spatial dependency. Model results indicate that R&D investment exerts a significant and stable direct positive effect on local patent output, underscoring the importance of increased R&D investment for generating local innovation outcomes. However, the spatial spillover effects of R&D investment exhibit significant volatility. Negative spillovers (siphoning effects) emerged in 2019, and although subsequent years saw a shift to positive spillovers, the overall effect showed a fluctuating downward trend. This indicates instability in interregional technology diffusion and knowledge sharing. Furthermore, GWR results strongly confirm that the impact of higher education and scientific personnel concentration on R&D intensity exhibits pronounced regional differences and spatial heterogeneity. This necessitates tailored R&D investment policies tailored to local conditions across regions. Addressing the current imbalance in innovation resources and significant capability gaps across eastern, central, and western regions, this paper proposes three institutional innovation initiatives: establishing a cross-regional patent pool sharing mechanism, developing blockchain-enabled digital technology trading platforms, and forming multi-stakeholder regional innovation alliances integrating government, industry, academia, research, and finance. These measures aim to promote coordinated industrial development across regions, enhance overall innovation capabilities, and secure a competitive edge in global technological competition.

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