Research on the Difference of Technological Innovation Capabilities of Regional High-tech Industries Based on Panel Data Clustering

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Received date: Aug. 22, 2025, Revision date: Sept. 25, 2025, Accepted: Oct. 10, 2025

ABSTRACT

The developmental level of high-tech industries bears a close connection to a region's overall competitiveness, and accurately identifying the differences in innovation capabilities during the R&D and transformation phases of these industries plays a vital role in developing targeted policies. Taking into account the features of panel data related to high-tech industries, this paper develops a grey matrix-type relational clustering model based on panel data by applying grey relational analysis. This model is used to assess the technological innovation capacities of high-tech industries across 30 provinces (including municipalities directly under the Central Government and autonomous regions) in China (with the Tibet Autonomous Region excluded) and identify variations from the two perspectives of "technological R&D" and "achievement transformation". The findings show that the general innovation capacity of China's high-tech industries remains relatively low, and there is a notable regional imbalance; the hierarchy of innovation capacities follows a pattern where eastern provinces/municipalities outperform central provinces/municipalities, which in turn are superior to northwestern provinces/municipalities. Furthermore, the two-phase clustering ultimately results in six provincial/municipal combination categories, laying a precise foundation for policy development.

Keywords: Technological Innovation, Regional Difference, Technology R&D; Achievement Transformation

1. Introduction

Serving as a cornerstone of the knowledge economy, a critical driver of economic growth, and the core of economic competition among nations, the high-tech industry has attracted significant focus from governments worldwide. As documented in the China High-Tech Industry Statistical Yearbook, the main operating income of China's high-tech industry in 2015 reached 2.35 times the figure in 2009, and its added value accounted for 22.6% of the manufacturing sector. Unlike traditional industries, the high-tech industry is distinguished by high R&D investment and strong penetrability; its competitiveness originates from technological innovation, while the advancement of innovation depends on increased investment in science and technology and the enhancement of innovation capacities.

Although the scale and intensity of R&D investment in China's high-tech industry have grown annually, prominent challenges persist, such as insufficient independent innovation capabilities and unbalanced regional development. Clarifying the current status and differences in innovation capabilities across provinces, and formulating differentiated development policies, are vital for advancing the optimization and upgrading of industrial structures and stimulating the rapid growth of high-tech industries.

2. Construction of an Evaluation Index System for the Innovation Capability of High-Tech Industries

Assessing the technological innovation capabilities of high-tech industries is a sophisticated systems engineering task. This assessment involves multiple factors, requiring the structured establishment of an evaluation index system from diverse perspectives and dimensions to reflect the industry's comprehensive innovation capabilities. The selected indicators should cover, to the greatest extent possible, all aspects that reflect the innovation capabilities of high-tech industries, aiming to comprehensively and objectively depict the current state of these capabilities. Thus, developing a scientific and rational evaluation index system is a key task in innovation capability assessment.

By reviewing relevant studies by domestic and international scholars on high-tech industry innovation capability evaluation systems, it is found that the construction of such systems remains incomplete and lacks consistent standards. Evaluation methods vary in characteristics and require optimization; meanwhile, research on inter-provincial differences in the technological innovation capabilities of high-tech industries is insufficient, and there is a shortage of phased studies focusing on these differences. This leads to ambiguity and inconsistencies in the development planning and decision-making of high-tech industries across provinces and municipalities.

Building on existing research, this study integrates the current development status of provincial-level high-tech industries in China, adheres to the principles of index system construction, and references relevant studies by domestic and international scholars. In line with the principles of scientificity, comprehensiveness, and data accessibility, a two-stage evaluation index system for the technological innovation capabilities of high-tech industries is established.

In the technological achievement transformation phase, evaluation indicators are chosen from three aspects-innovation achievement input, intermediate technology input, and industrialization benefits—which are denoted as respectively $x_1^1, x_2^1, ..., x_{14}^1$; their corresponding weights are denoted as $w_1^1, w_2^1, ..., w_{14}^1$. This index system is used to characterize and measure the technological transformation capabilities of high-tech industries at the provincial level during the technological achievement transformation phase. The specific evaluation indicators are presented in Table 1.

In the technological R&D stage, 14 evaluation indicators are selected from three dimensions—technological innovation input, technological innovation output, and innovation environment support—denoted as $x_1^1, x_2^1, ..., x_{14}^1$ respectively; their corresponding weights are denoted as $w_1^1, w_2^1, ..., w_{14}^1$. This system is used to measure the technological R&D level of provincial high-tech industries and characterize their innovation capabilities during the R&D phase(Alrawashdeh et al., 2024).

In the technological achievement transformation stage, evaluation indicators are selected from three aspects—innovation achievement input, intermediate technology input, and industrialization benefits—denoted as $x_1^2, x_2^2, ..., x_{14}^2$ respectively; their corresponding weights are denoted as $w_1^2, w_2^2, ..., w_{14}^2$. This system characterizes and measures the technological transformation capabilities of provincial high-tech industries during the achievement transformation phase. Specific indicators are shown in Table 1.

Table 1: Evaluation index system for technological innovation capability of high-tech industries

Technological R&D Stage		Technology achievement transformation stage	
First level indicator	**Secondary indicators**	**First level indicator**	**Secondary indicators**
Technological Innovation Input	Average number of employees x_1^0	**Investment in innovation results**	Number of patent applications x_1^2
	Number of companies with R&D activities x_2^1		Number of invention patent applications x_2^2
	Full-time equivalent of R&D personnel x_3^1		Number of enterprises x_3^2
	Internal expenditure on R&D funds x_4^1		Number of new product development projects x_4^2
	New product development expenditure x_5^1		Fixed asset investment x_5^2
Technological Innovation Output	Number of patent applications x_6^1	**Intermediate technology investment**	Number of valid invention patents x_6^2
	Number of invention patent applications x_7^1		Technology introduction funds x_7^2
	Number of valid invention patents x_8^1		Digestion and absorption expenses x_8^2
	Number of new product development projects x_9^1		Funding for purchasing domestic technology x_9^2
Innovation environment support	Add new fixed assets x_{10}^1		Technical transformation funds x_{10}^2
	Number of enterprises with R&D institutions x_{11}^1	**Industrialization benefits**	new product sales revenue x_{11}^2
	Number of R&D institutions x_{12}^1		export delivery value x_{12}^2
	R&D institution expenditure x_{13}^1		Profit amount x_{13}^2
	Value of instruments and equipment in R&D institutions x_{14}^1		

3. Data Sources and Research Methods

3.1. Data Sources

Assessing the technological innovation capabilities of high-tech industries is a complex task that depends on objective and accurate statistical data. The data used in this study are sourced from the China Statistical Yearbook (2009–2015), China Science and Technology Statistical Yearbook (2009–2015), and China High-Tech Industry Statistical Yearbook (2009–2015). For analysis, relevant high-tech industry data from 30 provinces (municipalities directly under the Central Government and autonomous regions) in China are selected, with the Tibet Autonomous Region not included due to incomplete data availability(Tseng et al., 2009).

3.2. Research Methods

Conventional approaches for evaluating the technological innovation capabilities of high-tech industries include the fuzzy assessment model, rough set technique, TOPSIS method, factor analysis, structural equation model, and DEA(Hsieh et al., 2003). However, these methods have drawbacks such as narrow application scopes and strong subjective interference. Moreover, they cannot fully tap into the information on regional high-tech industry development contained in panel data, which may lead to deviations between evaluation results and real-world scenarios.

To precisely distinguish the differences and individual traits of evaluation objects across various attributes, and improve the targeting of policy formulation and the effectiveness of scheme selection, this study leverages the unique advantages of the grey clustering method in addressing "information-poor" clustering problems (Hsieh et al., 2003). It integrates the spatio-temporal feature attributes of panel data, based on the basic principles of grey relational analysis and hierarchical clustering, and finally proposes a multi-index grey relational clustering method suitable for panel data.

Let there be a decision information system $S=\{U,A,V,C\}$ based on panel data, where $U=\left\{1,2,...,N\right\}$ represents the set of clustering objects; $A=\{a_1,a_2,...,a_m\}$ is the index set; $V=\cup v_{ij}^t(i=1,2,...,n;j=1,2,...,m;t=1,2,...T)$ is the value domain of panel data, in which \ v_{ij}^t is the observed value of clustering object i for index j at time t ; and $C=\left\{c_1,...,c_l,...,c_q\right\}(l=1,2,...,q)$ represents the set of spatiotemporal characteristic attributes of objects.

Definition 1 Let $x_{ij}(t)$ be the dimensionless measure value of the index value v_{ij}^t for index $j(j=1,2,...,m)$ of object $i(i=1,2,...,N)$ at time $t(t=1,2,...,T)$. For $i=1,2,...,n;j=1,2,...,m;t=1,2,...T$, if $\Delta x_{ij}(t)$, $\overline{x}_i(j)$, and $S_i(j)$ respectively denote the increment of the j -th index of object i at time t, the mean value of the j -th index, and the standard deviation, and satisfy $\mu_{ij}(t)=\dfrac{\Delta x_{ij}(t)}{x_{ij}(t)},\eta_i(j)=\dfrac{S_i(j)}{\overline{x}_i(j)}$ then the matrices are respectively called

$$x_i(t)=\begin{bmatrix} x_{i1}(1) & x_{i2}(1) & \dots & x_{ij}(1) & \dots & x_{im}(1) \\ x_{i1}(2) & x_{i2}(2) & \dots & x_{ij}(2) & \dots & x_{im}(2) \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ x_{i1}(t) & x_{i2}(t) & \dots & x_{ij}(t) & \dots & x_{im}(t) \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ x_{i1}(T) & x_{i2}(T) & \dots & x_{ij}(T) & \dots & x_{im}(T) \end{bmatrix},\quad i=1,2,\dots,N$$

$$\mu_i(t)=\begin{bmatrix} \mu_{i1}(2) & \mu_{i2}(2) & \dots & \mu_{ij}(2) & \dots & \mu_{im}(2) \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ \mu_{i1}(t) & \mu_{i2}(t) & \dots & \mu_{ij}(t) & \dots & \mu_{im}(t) \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ \mu_{i1}(T) & \mu_{i2}(T) & \dots & \mu_{ij}(T) & \dots & \mu_{im}(T) \end{bmatrix},\quad i=1,2,\dots,N$$

$$\eta_i=\begin{bmatrix} \eta_{i1} & \eta_{i2} & \dots & \eta_{ij} & \dots & \eta_{im} \end{bmatrix},\quad i=1,2,\dots,N$$

To be the absolute quantity level matrix, increment level matrix, and fluctuation level matrix of object i under panel data.

where $\Delta x_{ij}(t)=x_{ij}(t)-x_{ij}(t-1)$, $\overline{x}_i(j)=\dfrac{\sum_{t=1}^{T}x_{ij}(t)}{T}$, $S_i(j)=\dfrac{\sum_{t=1}^{T}(x_{ij}(t)-\overline{x}_i(t))^2}{T-1}$.

According to the spatio-temporal characteristics of panel data, this paper sets the spatio-temporal characteristic attributes of the research object as absolute quantity level, increment level, and fluctuation level, denoted as c_1,c_2,c_3 respectively. Then $l=1,2,3$ and $q=3$. Let $\gamma_{ij_l}(t)$ be the measurement value of object i at time t regarding the spatio-temporal characteristic attribute c_l of index j, which represents the attribute values of absolute quantity level, increment level, and fluctuation level spatio-temporal characteristics. Correspondingly, the object spatio-temporal characteristic matrix can be defined.

Definition 2 Let $\gamma_{ij_l}(t)$ denote the measurement value of object i for index j at time t under the spatio-temporal characteristic attribute c_l. For $\forall i\in U$, $\forall a_j\in A$, $c_l\in C$, $i=1,2,\dots,n; j=1,2,\dots,m; t=1,2,\dots T$, the matrix

$$\gamma_{i_l}(t)=\begin{bmatrix} \gamma_{i1_l}(1) & \gamma_{i2_l}(1) & \dots & \gamma_{ij_l}(1) & \dots & \gamma_{im_l}(1) \\ \gamma_{i1_l}(2) & \gamma_{i2_l}(2) & \dots & \gamma_{ij_l}(2) & \dots & \gamma_{im_l}(2) \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ \gamma_{i1_l}(t) & \gamma_{i2_l}(t) & \dots & \gamma_{ij_l}(t) & \dots & \gamma_{im_l}(t) \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ \gamma_{i1_l}(T) & \gamma_{i2_l}(T) & \dots & \gamma_{ij_l}(T) & \dots & \gamma_{im_l}(T) \end{bmatrix}$$

is the measurement value matrix of object i at time t with respect to indicator j_l for spatiotemporal feature attribute c_l.

Considering that grey relational analysis judges whether the connection is close based on the similarity degree of the geometric shapes of sequence curves, the grey relational analysis method can be used to measure the distance between research objects i and k with respect to index $j(j=1,2,...,m)$ under the time characteristic attribute set C (Thomas et al., 2011). Correspondingly, the grey relational coefficient between research objects i and k with respect to index j under the time characteristic attribute set C is:

$$d_{ik}^{j}=\frac{\min\limits_{i}\min\limits_{j} d_{ik}^{*j}+\rho\max\limits_{i}\max\limits_{j} d_{ik}^{*j}}{d_{ik}^{*j}+\rho\max\limits_{i}\max\limits_{j} d_{ik}^{*j}}$$

Correspondingly, the grey relational degree between objects i and k under the time characteristic attribute set C is:

$$d_{ik}^{C}=\sum_{j=1}^{m} w_j d_{ik}^{j}$$

where w_j is the weight of index $j(j=1,2,...,m)$ under the time characteristic attribute set C, $0\le w_j\le 1$, and $\sum_{j=1}^{m} w_j=1$.

Definition 3 Let d_{ik}^{C} denote the distance between decision-making objects i,k with respect to the set of spatio-temporal characteristic attributes C. For $\forall i,k\in U$, if $d_{ik}^{C}=d_{ki}^{C}$ holds, then the matrix

$$d=\begin{bmatrix} d_{11}^{C} & d_{12}^{C} & \cdots & d_{1k}^{C} & \cdots & d_{1n}^{C} \\ d_{21}^{C} & d_{22}^{C} & \cdots & d_{2k}^{C} & \cdots & d_{2n}^{C} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ d_{i1}^{C} & d_{i2}^{C} & \cdots & d_{ik}^{C} & \cdots & d_{in}^{C} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ d_{n1}^{C} & d_{n2}^{C} & \cdots & d_{nk}^{C} & \cdots & d_{nn}^{C} \end{bmatrix}$$

is the association distance matrix of multiple spatiotemporal feature attribute objects.

Definition 4 Let d be the distance matrix for objects with multi-attribute characteristics. For $\forall i,k\in U,C$, $\alpha\in[0,1]$, if $d_{ik}^{C}\ge\alpha$, then i,k are said to belong to the same class. Correspondingly, the classification of objects with multi-attribute characteristics under the critical value α is called the α -grey relational clustering of objects with multi-attribute characteristics.

α can be determined according to the requirements of practical problems(Thoma et al., 2011). . The closer α is to 1, the finer the classification is, and the relatively fewer objects are in each group; the smaller α is, the coarser the classification is, and the relatively more variables are in each group at this time.

4. Results and Discussion

4.1. Benchmark Regression Model

To gain an accurate understanding of the development status of regional high-tech industries and tackle the problem of regional imbalance, this study draws on statistical data from the China Statistical Yearbook, China Science and Technology Statistical Yearbook, and China High-Tech Industry Statistical Yearbook covering the period 2009–2015. It takes 30 provinces (municipalities directly under the Central Government, autonomous regions) in mainland China as the research subjects—with the Tibet Autonomous Region excluded due to partial missing data—and carries out empirical analysis by applying the established provincial-level technological innovation capability index system and grey matrix-type correlation degree clustering model. In the end, this study offers support for developing high-tech industry development policies and measures tailored to different provinces.

Based on previous research by the project team and expert evaluation, the indicator weights in the technological R&D stage are determined as follows: $w_1^1 = 0.1, w_2^1 = 0.12$, $w_3^1 = 0.13, w_4^1 = 0.09, w_5^1 = 0.1, w_6^1 = 0.11, w_7^1 = 0.05, w_8^1 = 0.03, w_9^1 = 0.04,$ $w_{10}^1 = 0.03, w_{11}^1 = 0.05, w_{12}^1 = 0.04, w_{13}^1 = 0.06, w_{14}^1 = 0.05$, and the weights of spatio-temporal characteristic attributes are $w_1^1=0.7, w_2^1=0.1, w_3^1=0.2$. Correspondingly, for the technological achievement transformation stage, the indicator weights are $w_1^2 = 0.3, w_2^2 = 0.11, w_3^2 = 0.2, w_4^2 = 0.05, w_5^2 = 0.03,$ $w_6^2 = 0.06, w_7^2 = 0.02, w_8^2 = 0.06,$ $w_9^2 = 0.01, w_{10}^2 = 0.04, w_{11}^2 = 0.05, w_{12}^2 = 0.01, w_{13}^2 = 0.06$, and the weights of spatio-temporal characteristic attributes are $w_1^2=0.8, w_2^2=0.1, w_3^2=0.1$. The matrix grey relational model can be used to calculate the grey relational degrees between provinces and municipalities in the technological R&D stage and the technological transformation stage.

In the technological R&D phase, clustering analysis divides 30 provinces/municipalities into three categories. Among these, eastern provinces/municipalities (including Beijing, Shanghai, Jiangsu, Guangdong, Shandong, etc.) possess the strongest technological R&D capacities, followed by central and western provinces/municipalities, while northwestern provinces/municipalities rank the weakest. This pattern stems from the eastern region's rich endowment of scientific and technological resources (e.g., universities and research institutions) and talent, as well as the high priority local governments place on R&D input. In contrast, central and western regions face insufficient R&D investment due to fund constraints and talent shortages; even though some of these provinces/municipalities have certain scientific and educational resources, they only reach a medium R&D level—primarily due to inadequate investment or insufficient government focus on scientific and technological R&D.

Meanwhile, in the technological achievement transformation phase, the 30 provinces/municipalities are also grouped into three categories via clustering: eastern provinces/municipalities have significantly leading achievement transformation capabilities, central and western regions are at a medium level, and northwestern provinces/municipalities lag far behind. Based on this, with technological R&D level as the x-axis and technological transformation capability as the y-axis, the three-category clustering results of the two phases theoretically form 9 capability combinations. By integrating the grey relational degree data and clustering results of each province/municipality in the two phases, a two-dimensional clustering map reflecting the technological innovation capabilities of provincial high-tech industries can be further constructed (see Figure 1).

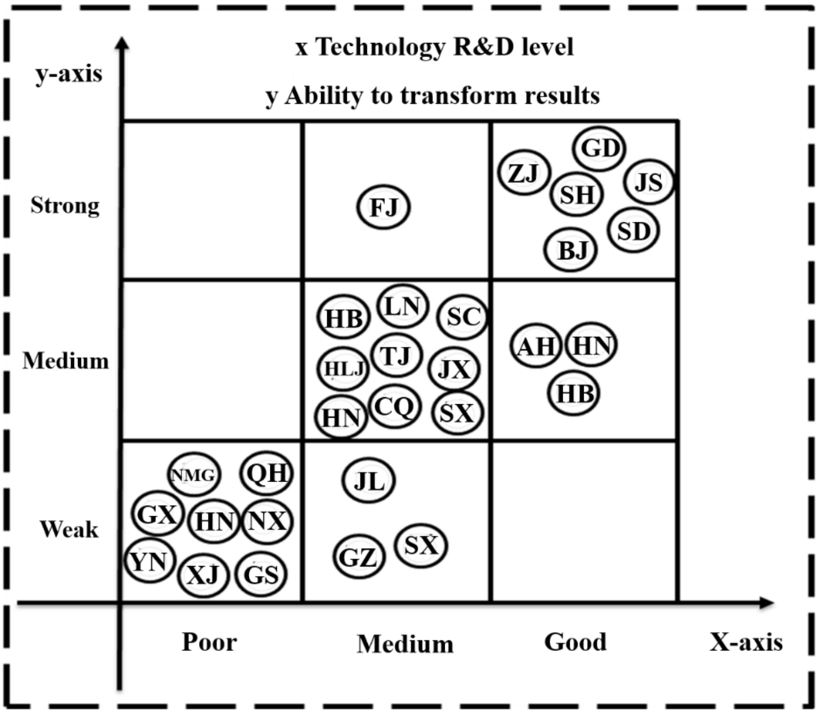

Figure 1. Two-stage clustering coordinate diagram

For the six existing combined categories, the distribution of provinces and municipalities is as follows: Category 1 (Strong R&D Level-Strong Achievement Transformation Capability): Provinces and municipalities like Beijing, Shanghai, Guangdong, Jiangsu, Zhejiang, and Shandong show robust technological innovation capabilities in both the technological R&D stage and the transformation stage. This is closely linked to their locational and resource advantages, as well as the great emphasis placed by local governments on the development of the high-tech industry. Category 2 (Strong R&D Level-Average Achievement Transformation Capability): Hubei, Hunan, and Anhui boast a relatively strong R&D capacity, yet their ability to transform scientific and technological achievements is merely at an average level. Category 3 (Average R&D Level-Strong Achievement Transformation Capability): Fujian Province is the sole member of this category. Although Fujian's R&D level is average, its capability to transform scientific and technological achievements has been relatively strong in recent years. This is primarily driven by factors like policy support from the local government and investment in technological services, which have greatly enhanced its achievement transformation capacity. Category 4 (Average R&D Level-Average Achievement Transformation Capability): Provinces and municipalities such as Tianjin, Shaanxi, Sichuan, Heilongjiang, Henan, and Hebei have average performance in both R&D and the transformation of scientific and technological achievements. Despite having considerable scientific and educational resources, these regions have not fully tapped their existing strengths—a situation linked to insufficient attention from local governments toward scientific and technological investment and transformation. Category 5 (Average R&D Level - Weak Achievement Transformation Capability): Jilin, Guizhou, and Shanxi feature an average R&D level alongside weak achievement transformation capacity, which is tied to their relatively inadequate investment in scientific and educational resources. Category 6 (Low R&D Level-Weak Achievement Transformation Capability): Provinces and municipalities including Xinjiang, Gansu, Qinghai, Yunnan, and Hainan rank the lowest in both R&D and transformation capabilities. This is ascribed to their comparatively scarce regional resources and insufficient attention from local governments.

Empirical analysis shows that the overall technological innovation capability of China's high-tech industry is generally weak: most provinces/municipalities have average or weak R&D and transformation capabilities, while only a few have strong capacities in both areas. Additionally, the technological innovation capability of China's high-tech industry exhibits significant regional differences and imbalance. Eastern provinces/municipalities perform well in both R&D and transformation, followed by central regions, with northwestern regions being the weakest. The gap between eastern and central provinces/municipalities is relatively large, while the gap between central and northwestern regions is not significant.

5. Conclusions

The core of competition in the high-tech industry resides in technological competition. Only by boosting the innovation capacities of regional high-tech industries and grasping core key technologies can we truly build industrial strengths and promote the rapid, healthy, and sustainable development of China's high-tech industry. Based on the current status and differences in the technological innovation capabilities of high-tech industries across Chinese provinces/municipalities, differentiated development strategies should be implemented:

For Type 1 provinces/municipalities (with distinctive advantages, complete industrial chains, and an international competitive foundation): Intensify R&D input, policy support, and technological services; enhance original innovation and sustainable development capacities; incorporate global innovation resources; and focus on high-end advanced manufacturing to foster new competitive strengths.

For Type 2 provinces/municipalities (solid industrialization foundation but insufficient transformation capabilities): Take high-tech zones and industrial bases as carriers to improve the efficiency of integrated innovation resource utilization; optimize the innovation chain of advantageous industries to form characteristic industrial clusters; and strive for national leadership in key field research.

For Type 3 provinces/municipalities (strong transformation capabilities but average R&D level): Rely on major projects to tackle key technologies; increase investment in talent and R&D; and enhance original innovation capacities to promote industrial upgrading and form field-specific characteristic clusters.

For Type 4 provinces/municipalities (small economic scale and low industrial level): Increase investment based on existing resources; formulate scientific plans to advance traditional industry transformation; and build emerging industry platforms to shift industries from "resource-led" to "diversified and comprehensive".

For Type 5 provinces/municipalities (scarce scientific and technological resources and weak transformation capabilities): Strengthen innovation awareness and cultural development; increase R&D and service investment; improve the industry-university-research system; and optimize the policy environment to drive innovation capacity improvement through industrial development.

For Type 6 provinces/municipalities (primary stage of industrialization): Take characteristic advantageous industries and strategic emerging industries as carriers to increase government investment; leverage the radiating role of central cities and science and technology parks; deepen horizontal regional cooperation; strengthen vertical industrial links between eastern and western regions; and focus on addressing common development challenges.

Funding

(1) The work is supported by the Henan Provincial Philosophy and Social Sciences Education Strengthening Program (Grant No. 2025JYQS0394).

(2) The work is supported by the General Research Project of Humanities and Social Sciences in Henan Universities (Grant No. 2026-ZZJH-206).

(3) The work is supported by the Educational Financial Management Research Project of the Henan Provincial Department of Education (Grant No. 2024C48).

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