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

Yiheng Guo

School of Finance and Accounting, Henan University of Animal Husbandry and Economy, China

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**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

High-tech industries are widely regarded as important carriers of knowledge-based growth, industrial upgrading, and regional competitiveness because their development depends heavily on R&D investment, technology accumulation, and innovation-output transformation (Griliches, 1994; Tu et al., 2023; Xu, 2023). In China, high-tech manufacturing has continued to expand rapidly: in 2024, the value added of high-tech manufacturing enterprises above designated size increased by 8.9% year on year, exceeding the growth rate of all industrial enterprises above designated size, and accounted for 16.3% of the value added of industries above designated size (National Bureau of Statistics of China, 2025). High-tech industry investment also increased by 8.0% in 2024, indicating the continued strengthening of China's innovation-driven industrial transformation. Unlike traditional industries, high-tech industries are characterized by high R&D intensity, strong knowledge spillovers, and close links between technological innovation and industrial competitiveness.

Although the scale and intensity of R&D investment in China?s high-tech industry have increased, the literature continues to show uneven regional development and substantial differences in innovation capacity across Chinese provinces (Tu et al., 2023; Xu, 2023; Yang & Xue, 2010). Recent studies also indicate that less-developed northwestern provinces still face structural constraints in innovation platforms, market-oriented technology outputs, and high-tech enterprise capabilities (Liu et al., 2025). Clarifying the current status and interprovincial differences in innovation capabilities, and formulating differentiated development policies, are therefore important for industrial upgrading and the coordinated development 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 complex multi-index evaluation task. Existing studies usually construct indicator systems around R&D input, innovation output, innovation environment, industrialization, and efficiency dimensions in order to capture both the resource base and the realized performance of innovation activities (Chen & Huang, 2004; Li & Su, 2012; Wang, Lu, & Chen, 2008). A scientific and rational evaluation index system is therefore a prerequisite for measuring provincial high-tech industries in a comparable way.

Prior research has evaluated high-tech industry development and innovation capability from several perspectives, including multiple-criteria evaluation of science parks, firm-level technological innovation capability, rough-set evaluation of R&D processes, regional innovation capability, and spatial evolution of China?s high-tech industries (Chen, Wu, & Lin, 2006; Tu et al., 2023; Wang, Chin, & Tzeng, 2010; Wang, Lu, & Chen, 2008; Yang & Xue, 2010). However, the existing literature still pays insufficient attention to the simultaneous distinction between the R&D stage and the achievement transformation stage, especially when provincial panel data are used to extract interregional differences. This creates a need for a two-stage evaluation framework that can integrate both temporal changes and cross-sectional regional heterogeneity (Li et al., 2025; Xu, 2023).

Building on these studies and the current development status of provincial-level high-tech industries in China, this study follows the principles of scientificity, comprehensiveness, comparability, and data accessibility. It establishes a two-stage evaluation index system for technological innovation capability, distinguishing between the technological R&D stage and the technological achievement transformation stage.

The two phases are treated as distinct but connected components of technological innovation capability. The R&D stage captures knowledge creation and innovation-resource accumulation, whereas the achievement transformation stage captures the conversion of technological outputs into industrial and market performance.

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

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). The sample includes high-tech industry data from 30 provinces, municipalities directly under the Central Government, and autonomous regions in mainland China. The Tibet Autonomous Region is excluded because several key indicators required for constructing a balanced panel are incomplete. The statistical-yearbook data are used consistently for both the R&D-stage and achievement-transformation-stage indicators.

### 3.2. Research Methods

Conventional approaches for evaluating technological innovation capability include fuzzy comprehensive assessment, rough-set analysis, TOPSIS, factor analysis, structural equation modeling, and DEA-based efficiency evaluation (Cheng & Yuan, 2012; Liu, 2013; Tseng & Chiu, 2009; Wang, Chin, & Tzeng, 2010). These methods are useful in many cross-sectional, firm-level, or efficiency-oriented settings. However, when the research objective is to classify provincial high-tech industries by simultaneously considering absolute levels, increments, and fluctuations in panel data, a method that can handle multi-index, incomplete-information, and spatio-temporal comparison problems is needed.

To identify differences among evaluation objects across multiple attributes and improve the targeting of policy formulation, this study adopts a grey matrix-type relational clustering model based on panel data. Grey relational analysis is appropriate for comparing the geometric similarity of sequences under limited information, and grey clustering can further classify objects with similar multi-attribute characteristics (Che & Yu, 2010; Li & Su, 2012; Xu, 2023). The method integrates the spatio-temporal feature attributes of panel data with the principles of grey relational analysis and hierarchical clustering, making it suitable for evaluating provincial high-tech industries over time.

The empirical procedure is as follows. First, raw panel indicators are standardized to eliminate dimensional differences. Second, absolute quantity, increment, and fluctuation matrices are constructed for each province and indicator. Third, grey relational coefficients are calculated under each spatio-temporal characteristic attribute. Fourth, indicator weights and spatio-temporal attribute weights are used to aggregate grey relational degrees. Fifth, the association distance matrix is generated and the alpha threshold is applied to classify provinces. Finally, the two-stage R&D and achievement-transformation results are combined to form the provincial capability categories.

Let there be a decision information system $S=\{U,A,V,C\}$ based on panel data, where $U=\{1,2,...,N\}$ 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 $\backslash v_{ij}^t$ is the observed value of clustering object $i$ for index $j$ at time $t$; and $C=\{c_1,...,c_l,...,c_q\}(l=1,2,...,q)$ 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 $\Delta x_{ij}(t)$, $\bar{x}_i(j)$, 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 $\mu_{ij}(t)=\dfrac{\Delta x_{ij}(t)}{x_{ij}(t)}$, $\eta_i(j)=\dfrac{S_i(j)}{\bar{x}_i(j)}$ 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 $\Delta x_{ij}(t)=x_{ij}(t)-x_{ij}(t-1)$, $\bar{x}_i(j)=\dfrac{\sum_{t=1}^{T}x_{ij}(t)}{T}$, $S_i(j)=\dfrac{\sum_{t=1}^{T}(x_{ij}(t)-\bar{x}_i(t))^2}{T-1}$.

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 $j(j=1,2,\ldots,m)$ 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:

$$d_{ik}^{j}=\frac{\min_{i}\min_{j}d_{ik}^{*j}+\rho\max_{i}\max_{j}d_{ik}^{*j}}{d_{ik}^{*j}+\rho\max_{i}\max_{j}d_{ik}^{*j}}$$

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 $j(j=1,2,\ldots,m)$ 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 $\alpha$ is called the $\alpha$-grey relational clustering of objects with multi-attribute characteristics.

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

The critical value alpha determines the granularity of grey relational clustering. A larger alpha produces finer classifications, whereas a smaller alpha produces coarser classifications. In this study, alpha should be selected according to both the distribution of grey relational distances and the interpretability of the resulting provincial groups; the selected value must be reported explicitly so that the empirical clustering can be reproduced (Xu, 2023).

## 4. Results and Discussion

4.1. Grey Relational Clustering Results

To gain an accurate understanding of the development status of regional high-tech industries and the sources of regional imbalance, this study uses statistical data from the China Statistical Yearbook, China Science and Technology Statistical Yearbook, and China High-Tech Industry Statistical Yearbook covering 2009-2015. It takes 30 provinces, municipalities directly under the Central Government, and autonomous regions in mainland China as the research subjects, excluding Tibet because of incomplete panel data, and applies the established two-stage technological innovation capability index system and grey matrix-type relational clustering model.

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 the 30 provinces/municipalities into three categories. Eastern provinces and municipalities, including Beijing, Shanghai, Jiangsu, Guangdong, and Shandong, generally show the strongest technological R&D capacities, followed by central provinces, while several northwestern provinces rank the weakest. This pattern is consistent with recent evidence that China?s high-tech industry innovation capability has improved but remains spatially unbalanced, with stronger innovation resources and transformation conditions concentrated in more developed eastern regions (Tu et al., 2023; Xu, 2023).

In the technological achievement transformation phase, the 30 provinces/municipalities are also grouped into three categories. Eastern provinces/municipalities have stronger achievement transformation capabilities, central and western regions are at a medium level, and northwestern provinces/municipalities lag behind. 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 nine 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 constructed (see Figure 1).

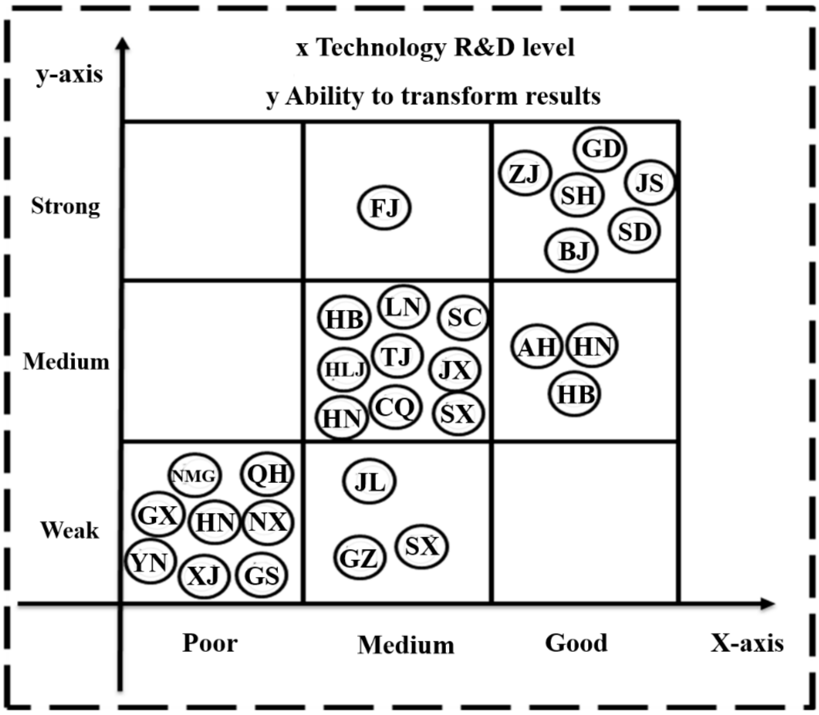


**Figure 1.** Two-stage clustering coordinate diagram

For the six observed combined categories, the distribution of provinces and municipalities is as follows. Category 1, strong R&D level and strong achievement transformation capability, includes Beijing, Shanghai, Guangdong, Jiangsu, Zhejiang, and Shandong. These regions benefit from stronger innovation resources, industrial chains, and high-tech industrial agglomeration. Category 2, strong R&D level and average achievement transformation capability, includes Hubei, Hunan, and Anhui, where the main task is to improve the conversion of R&D outputs into industrialized results. Category 3, average R&D level and strong achievement transformation capability, includes Fujian, suggesting that transformation services and industrial support can compensate for relatively moderate R&D input. Category 4, average R&D level and average achievement transformation capability, includes Tianjin, Shaanxi, Sichuan, Heilongjiang, Henan, and Hebei. Category 5, average R&D level and weak achievement transformation capability, includes Jilin, Guizhou, and Shanxi. Category 6, low R&D level and weak achievement transformation capability, includes Xinjiang, Gansu, Qinghai, Yunnan, and Hainan. Studies on high-tech clusters, industrial agglomeration, and regional innovation show that agglomeration effects, innovation platforms, and differentiated regional policies are important for improving innovation capacity and transformation efficiency (Bao & Li, 2023; Ge et al., 2023; Yang, 2024).

Empirical analysis shows that the overall technological innovation capability of China?s high-tech industry remains uneven: most provinces/municipalities have average or weak R&D and transformation capabilities, while only a few have strong capacities in both stages. The results also confirm significant regional differences, with eastern provinces/municipalities performing better in both R&D and transformation, central regions occupying an intermediate position, and several northwestern regions remaining relatively weak. This finding is consistent with recent provincial and regional studies that identify persistent spatial imbalance in China?s innovation capacity (Liu et al., 2025; Tu et al., 2023; Xu, 2023).

## 5. Conclusions

The findings indicate that improving the innovation capacity of regional high-tech industries requires policies that match the two-stage capability structure of each provincial group. The following recommendations are therefore derived from the clustering results: provinces with strong R&D but weaker transformation should focus on technology transfer and industrialization platforms; provinces with weak R&D foundations should strengthen innovation inputs, R&D institutions, and high-tech enterprise capabilities; and provinces with both weak R&D and weak transformation should prioritize basic innovation infrastructure and regional cooperation. These directions are consistent with evidence that high-tech industrial agglomeration, innovation districts, and producer-service co-agglomeration can influence regional innovation capacity and efficiency (Bao & Li, 2023; Ge et al., 2023; Peng et al., 2022; Yang, 2024).

For Type 1 provinces/municipalities, which have distinctive advantages, complete industrial chains, and an international competitive foundation, policy should focus on maintaining high R&D input, strengthening original innovation, improving technological services, and integrating global innovation resources. These regions should use their existing agglomeration advantages to move toward high-end advanced manufacturing and globally competitive innovation networks.

For Type 2 provinces/municipalities, which have a solid R&D foundation but insufficient transformation capability, high-tech zones and industrial bases should be used as carriers to improve the efficiency of innovation-resource integration. Policy should focus on technology transfer, pilot-scale testing, enterprise-university-research collaboration, and the conversion of R&D outputs into market-oriented products.

For Type 3 provinces/municipalities, which have strong transformation capability but an average R&D level, major projects and key technology programs should be used to strengthen original innovation. Increasing investment in talent, R&D institutions, and enterprise R&D platforms can help these regions upgrade from transformation-oriented growth to innovation-source growth.

For Type 4 provinces/municipalities, which have average performance in both R&D and transformation, policy should first identify the weakest indicators within the two-stage index system and then increase investment in targeted innovation resources. These regions should combine traditional industry transformation with emerging-industry platform construction to avoid remaining at a medium-capability equilibrium.

For Type 5 provinces/municipalities, which have scarce scientific and technological resources and weak transformation capability, policy should strengthen innovation awareness, improve R&D and service investment, build industry-university-research collaboration mechanisms, and optimize the local policy environment. The priority is to improve the transformation of existing innovation resources into industrialized outputs.

For Type 6 provinces/municipalities, which are at a relatively early stage of high-tech industrial development, policy should increase basic R&D investment, improve innovation platforms, support characteristic advantageous industries and strategic emerging industries, and strengthen horizontal regional cooperation and vertical industrial links between eastern and western regions. Recent evidence on less-developed northwestern provinces suggests that R&D institutions, higher education institutions, high-tech enterprises, and market-oriented technology outputs are key factors for improving regional innovation capacity (Liu et al., 2025).

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