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Comparative Study on the Efficiency of Scientific and Technological Innovation and the Redundancy of Investment

-- Based on the Cross-sectional Data of 30 Provinces, Municipalities and Autonomous Regions

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Abstract

To enhance scientific and technological innovation efficiency and regional development in the digital era, this study examines innovation efficiency and input redundancy across 30 Chinese provinces, optimizing digital capital input and resource allocation. Using an input-oriented BCC-DEA model, an evaluation system for digital access and R&D capability measures 2022 data. Results show only 10 provinces were efficient, with Guizhou, Sichuan, and Chongqing at 0.410 efficiency versus Beijing, Shanghai, and Tianjin at 1.000, indicating significant regional disparities. Only 13 regions had zero redundancy, while 17 had input redundancy, particularly in digital R&D capability. The Chinese government should adjust science and technology policies and optimize resource allocation, while provinces should implement region-specific policies based on local redundancy and endowments.

Keywords

Efficiency of Technological Innovation; BCC-DEA Model; Input Redundancy.

1. Introduction

Technological innovation is crucial for enhancing regional competitiveness and achieving coordinated, sustainable development in regional economies [1]. It boosts economic efficiency, optimizes industrial outcomes, and drives industrial upgrading, helping China overcome development bottlenecks, shift from extensive growth, and transition to a technology-driven powerhouse. This approach addresses "chokepoint" challenges from Western countries and secures technological initiative [2]. The "14th Five-Year National Science and Technology Innovation Plan" emphasizes self-reliance in science and technology, with innovation at the core for international development and progress. In recent years, Chinese provinces have significantly increased investments in technological innovation, including funding for talent, capital, and infrastructure.

With rising investment, output has grown, but it is essential to evaluate whether these investments lead to efficient output and full utilization of resources. Innovation efficiency reflects the allocation and operational capabilities of scientific and technological resources in a region [3]. This paper references the DEA method for efficiency evaluation, adopting the input-oriented BCC-DEA model with 2022 data from 30 provinces to measure innovation efficiency under digital capital investment.

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2. Literature Review

2.1. Methods for Measuring the Efficiency of Scientific and Technological Innovation

Technological innovation efficiency denotes the ratio of inputs to outputs within innovation processes, illustrating resource usage and innovative capabilities. Present investigations emphasize measurement techniques, geographical disparities, and determinants. Measurement approaches involve parametric methods, such as Stochastic Frontier Analysis (SFA), and non-parametric methods, like Data Envelopment Analysis (DEA), with DEA frequently employed for its proficiency in managing varied inputs and outputs across different units [4].

In 1978, Charnes, Cooper, and Rhodes developed the Data Envelopment Analysis (DEA) method to assess inter-sectoral efficiency, with their initial model termed the CCR Model. Later in 1984, Banker, Charnes, and Cooper refined the DEA framework by introducing the BCC Model, which assumed variable returns to scale. Thus, the DEA framework encompasses both the CCR and BCC models.Applying the CCR-DEA model to gauge innovation efficiency across multiple Chinese regions, studies identified a general decline from eastern to western to central zones, where the central region's efficiency was substantially inferior to that of eastern and western areas [5]. Employing CCR-DEA and BCC-DEA models to assess scientific and technological innovation efficiency, findings indicated that resource distribution for such efficiency in certain regions requires further refinement [6].

2.2. Regional Evaluation of the Efficiency of Scientific and Technological Innovation

Domestic research primarily focuses on in-depth analysis of the efficiency of scientific and technological innovation across China's 31 provinces (municipalities, autonomous regions), with comprehensive evaluations of regional correlations or disparities. Many scholars have also studied China's major economic belts, such as the Yangtze River Economic Belt, the Three Major Economic Belts, and the Belt and Road-related economic belts. The DEA method was employed to measure the efficiency of scientific and technological innovation in provinces and municipalities along the Yangtze River Economic Belt, analyzing regional differences [7]. The DEA model was further applied to investigate the disparities in the efficiency of scientific and technological innovation among 17 provinces (municipalities, autonomous regions) along China's Belt and Road from 2012 to 2016 [8]. Existing research mainly focuses on the national level and major economic belts, lacking comparative studies of provinces, municipalities, and autonomous regions with higher levels of scientific and technological innovation. Shanghai, Tianjin, Beijing, and Guangdong are important regions in China's scientific and technological innovation, showing significant differences in economic development levels and talent reserves. Therefore, it is necessary to conduct in-depth analyses of their respective characteristics and development trends. Based on this, this paper measures and evaluates the efficiency of scientific and technological innovation in 30 provinces, municipalities, and autonomous regions in 2022, excluding the Tibet Autonomous Region, Hong Kong Special Administrative Region, Macao Special Administrative Region, and Taiwan Province.

3. Evaluation Index System and Model of Scientific and Technological Innovation Efficiency

3.1. Indicator Selection and Data Sources

This study employs digital capital as the metric for measuring technological innovation investment, which represents the aggregate of external digital technologies and capabilities

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possessed by organizations or individuals. Drawing on the innovation efficiency framework developed by scholars Yuan Yongyi and Yuan Qinjian [8], we construct a digital capital evaluation system through two dimensions: digital connectivity levels and R&D capabilities in digital technology. The evaluation focuses on measuring innovation outputs through two key dimensions-knowledge and technological achievements, and economic output-as detailed in Table 1.

Table 1. Input-output indicators of scientific and technological innovation in China's provinces

Type	Primary indicator	Secondary indicator	Third-level indicator	Data sources
Indicators for the input in scientific and technological innovation	digital capital	Digital access level	Number of internet broadband access ports (in ten thousand)	China Statistical Yearbook 2022
			Mobile internet traffic (10,000 GB)	
		Digital technology R&D capabilities	R&D expenditure in software and information technology services (in billions of yuan)	Annual Statistics of Software and Information Technology Services in 2022
			Software and information technology services R&D personnel (in person)	
Indicators for the output in scientific and technological innovation	Knowledge and technological achievements	Knowledge and Technology Output	Number of patents granted（piece）	2022 Annual Report on Intellectual Property Statistics
	economic output	value added of new product	Sales revenue from new product sales of industrial enterprises (in billions of yuan)	China Science and Technology Statistical Yearbook 2022

3.2. Evaluation Model

3.2.1. BCC-DEA Model

Data Envelopment Analysis (DEA) eliminates the need to define specific production functions or weights. It assesses multi-input and multi-output systems to evaluate the efficiency of an evaluated sector's input-output relationship, thereby avoiding errors caused by predefined weights or assumptions about production functions. This approach yields more objective results [9]. While both CCR and BCC models can measure efficiency within a single period, the BCC model assumes variable returns to scale and is better suited for cross-sectional data analysis [10]. In this study, we employ an input-oriented BCC-DEA model, as outlined in the following formula.

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$$\begin{cases} \qquad\qquad min\theta_k \\ s.t. \quad \sum_{j=1}^{n}\lambda_j\chi_{ij}+S_{ik}^{-}=\theta_k\chi_{ik} \\ \qquad \sum_{j=1}^{n}\lambda_j\, y_{rj}-S_{rk}^{+}=y_{rk} \\ \qquad \sum_{j=1}^{n}\lambda_j=1, j=1,\ldots\ldots,\ n \\ \qquad S_{ik}^{-}\geq 0, S_{rk}^{+}\geq 0 \\ \qquad i=1,2,\ldots\ldots,m; r=1,2,\ldots\ldots,s. \end{cases} \tag{1}$$

Vrste is the pure technical efficiency, Scale is the scale efficiency, and Crste=Vrste×Scale is the comprehensive technical efficiency. Efficiency is 1 for relative efficiency, and less than 1 for relative inefficiency.

3.2.2. Calculation of the Redundancy Ratio

Based on the DEA-BBC model, the input redundancy analysis of DMUs is conducted, as shown in the following formula:

$$I_{mi}=S_{j}^{-}{}_{mi}/X_{mi}. \tag{2}$$

$S_{j}^{-}{}_{mi}$ denotes the redundancy of the m-th input in the i-th decision-making unit, X_{mi} represents the input quantity of the m-th input in the i-th decision-making unit, and I_{mi} is the input redundancy ratio. When the input redundancy ratio is 0, the decision-making unit is valid; if at least one input factor has a non-zero redundancy ratio, the decision-making unit is invalid or weakly valid.

4. Empirical Results Analysis

4.1. Analysis of the Efficiency of Science and Technology Innovation in 30 Provinces (Municipalities and Autonomous Regions) of China

The comprehensive technical efficiency averaged 0.777 across 30 provinces (municipalities, autonomous regions) in China, with pure technical efficiency at 0.823 and scale technical efficiency at 0.940. Table 1 presents the BCC-DEA model analysis results for these regions. Comparative analysis reveals that Anhui, Guangdong, Jiangsu, Jiangxi, Qinghai, Zhejiang, Beijing, Tianjin, Shanghai, and Inner Mongolia (10 provinces/municipalities/autonomous regions) achieved a comprehensive technical efficiency of 1, indicating strong support from digital capital for technological innovation. These regions demonstrate significant driving force of digital capital in innovation advancement. Notably, Guangdong, Zhejiang, Beijing, Tianjin, and Shanghai exhibit higher technological development levels, where high-end network equipment, skilled R&D personnel, and substantial R&D funding contribute to enhanced innovation efficiency. While Hebei, Henan, and Ningxia achieved pure technical efficiency at the efficient state, their scale technical efficiency remained inefficient, suggesting that although digital capital positively promotes innovation, its utilization efficiency weakens its catalytic effect. Other provinces failed to effectively leverage digital capital in both technical efficiency and scale benefits, with Guizhou, Sichuan, and Chongqing ranking at the bottom three. This indicates that there are significant regional disparities in China's scientific and technological innovation efficiency [11]. For instance, municipalities like Beijing and Shanghai, along with southeastern coastal provinces such as Jiangsu, Zhejiang, and Guangdong, are recognized as effective units with high innovation efficiency. In contrast, central and western provinces and autonomous regions, including Gansu, Guizhou, and Xinjiang, are mostly classified as ineffective units, meaning their innovation efficiency lags behind that of the more economically developed southeastern provinces and municipalities.

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Based on the changes of returns to scale, the returns to scale of Hebei, Henan, Sichuan and Guangxi are decreasing, which indicates that there is excessive digital capital input in these four regions. The returns to scale of other provinces, municipalities and autonomous regions are constant or increasing, among which the regions with increasing returns to scale account for 53.3%, which indicates that the development of scientific and technological innovation in these provinces still needs more digital capital resources.

Table 2. DEA-BCC model measurement results of 30 provinces (municipalities and autonomous regions) in China

Area	Crste	Vrste	Scale	Return of Scale
Anhui	1.000	1.000	1.000	invariant
Fujian	0.785	0.789	0.996	Increment
Gansu	0.790	0.809	0.977	Increment
Guangdong	1.000	1.000	1.000	invariant
Guizhou	0.454	0.498	0.911	Increment
Hainan	0.501	0.808	0.621	Increment
Hebei	0.965	1.000	0.965	Decreasing
Henan	0.772	1.000	0.772	Decreasing
Heilongjiang	0.863	0.996	0.894	Increment
Hubei	0.733	0.745	0.984	Increment
Hunan	0.769	0.777	0.990	Increment
Jilin	0.598	0.717	0.834	Increment
Jiangsu	1.000	1.000	1.000	invariant
Jiangxi	1.000	1.000	1.000	invariant
Liaoning	0.571	0.577	0.990	Increment
Qinghai	1.000	1.000	1.000	invariant
Shandong	0.810	0.833	0.972	Increment
Shanxi	0.751	0.788	0.953	Increment
Shaanxi	0.456	0.485	0.939	Increment
Sichuan	0.410	0.411	0.998	Increment
Yunnan	0.761	0.763	0.998	Decreasing
Zhejiang	1.000	1.000	1.000	invariant
Chongqing	0.402	0.555	0.724	Increment
Beijing	1.000	1.000	1.000	invariant
Tianjin	1.000	1.000	1.000	invariant
Shanghai	1.000	1.000	1.000	invariant
Ningxia	0.819	1.000	0.819	Increment
Nei Mongol	1.000	1.000	1.000	invariant
Xinjiang	0.531	0.578	0.920	Increment
Guangxi	0.578	0.608	0.958	Decreasing
Average	0.777	0.823	0.940	

4.2. Analysis of Redundant Investment in Science and Technology in 30 Provinces (Municipalities and Autonomous Regions) of China

Table 3 illustrates the adjustment trends of evaluation indicators for scientific and technological innovation output and input across China's 30 provinces (including municipalities and autonomous regions). The first two values indicate output status: 0 signifies sufficient output, while values above 0 indicate insufficient output. The subsequent four values

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reflect input surplus conditions: 0 denotes no relative surplus. As shown in Table 3, all 17 provinces (municipalities and autonomous regions) -Fujian, Gansu, Guizhou, Hainan, Heilongjiang, Hubei, and Hunan-exhibit both output insufficiency and input surplus. Regions with output insufficiency should enhance production capacity, while those with input surplus need to improve resource utilization efficiency.

Table 3. China's 30 provinces (municipalities, autonomous regions) scientific and technological innovation output, input slack variables

Indicators	Number of patents granted	Sales revenue from new product sales of industrial enterprises (in billions of yuan)	Number of internet broadband access ports (in ten thousand)	Mobile internet traffic (10,000 GB)	R&D expenditure in software and information technology services (in billions of yuan)	Software and information technology services R&D personnel (in person)
Anhui	0.000	0.000	0.000	0.000	0.000	0.000
Fujian	0.000	4542.444	319.289	0.000	0.000	23230.713
Gansu	0.000	1803.475	0.000	8536.655	0.000	574.982
Guangdong	0.000	0.000	0.000	0.000	0.000	0.000
Guizhou	0.000	2663.360	0.000	98792.913	31.593	0.000
Hainan	0.000	593.527	172.619	0.000	21.131	327.972
Hebei	0.000	0.000	0.000	0.000	0.000	0.000
Henan	0.000	0.000	0.000	0.000	0.000	0.000
Heilongjiang	0.000	3467.294	702.259	0.000	0.000	1147.635
Hubei	0.000	0.000	148.574	0.000	0.000	57396.911
Hunan	15345.490	0.000	0.000	186740.063	0.000	3578.969
Jilin	0.000	803.771	213.114	0.000	0.000	2517.643
Jiangsu	0.000	0.000	0.000	0.000	0.000	0.000
Jiangxi	0.000	0.000	0.000	0.000	0.000	0.000
Liaoning	0.000	628.001	377.173	0.000	0.000	48536.200
Qinghai	0.000	0.000	0.000	0.000	0.000	0.000
Shandong	83220.224	0.000	253.958	0.000	0.000	24995.868
Shanxi	0.000	1143.692	592.146	0.000	0.000	466.219
Shaanxi	0.000	2257.617	0.000	18653.965	0.000	10037.010
Sichuan	0.000	5549.572	0.000	21203.948	0.000	0.000
Yunnan	0.000	3982.304	6.452	264642.009	0.000	4797.189
Zhejiang	0.000	0.000	0.000	0.000	0.000	0.000
Chongqing	9996.301	0.000	0.000	0.000	37.937	25845.073
Beijing	0.000	0.000	0.000	0.000	0.000	0.000
Tianjin	0.000	0.000	0.000	0.000	0.000	0.000
Shanghai	0.000	0.000	0.000	0.000	0.000	0.000
Ningxia	0.000	0.000	0.000	0.000	0.000	0.000
Nei Monggol	0.000	0.000	0.000	0.000	0.000	0.000
Xinjiang	0.000	1965.586	81.121	0.000	0.000	117.912
Guangxi	0.000	3615.374	196.082	38102.500	0.000	742.577
Average	3618.734	1100.534	102.093	21222.402	3.022	6810.429

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Based on the DEA model and input redundancy ratio formula, we can further analyze the specific technological innovation input redundancy ratios of provinces, municipalities, and autonomous regions, as shown in Table 4. The comprehensive redundancy ratios for digital access levels and digital technology R&D capabilities were calculated by applying equal weighting to the redundancy metrics of these two input indicators. The results indicate that China's overall digital technology R&D capabilities exhibit significant redundancy, with an average redundancy ratio of 12.98% in 2022. This may be attributed to the overestimation of input quantities due to excessive R&D funding and personnel allocation, as well as potential inefficiencies in R&D expenditure utilization and workforce productivity. Regarding digital access levels, the overall redundancy ratio in 2022 was 5.28%, notably lower than the comprehensive redundancy ratio for digital technology R&D capabilities.

Table 4. Redundancy of input in science and technology innovation in 30 provinces (municipalities and autonomous regions) of China

Proportion	Redundancy ratio of internet broadband access ports (%)	Redundant mobile internet traffic percentage (%)	Digital access level comprehensive redundancy ratio (%)	Redundancy ratio of R&D expenditure in software and information technology services (%)	Redundancy ratio of R&D personnel in software and information technology services (%)	Comprehensive redundancy ratio of digital technology R&D capabilities (%)
Fujian	8.57	0	4.29	0	24.14	12.57
Gansu	0	1.79	0.90	0	32.21	16.11
Guizhou	0	11.17	5.59	38.82	0	19.41
Hainan	16.52	0	8.26	57.51	11.88	34.70
Heilongjiang	31.93	0	15.97	0	23.82	11.91
Hubei	3.65	0	1.83	0	34.85	17.43
Hunan	0	15.81	7.91	0	8.44	4.22
Jilin	11.64	0	5.82	0	24.21	12.11
Liaoning	10.95	0	5.48	0	41.36	20.68
Shandong	3.41	0	1.71	0	7.96	3.98
Shanxi	21.45	0	10.73	0	14.09	7.05
Shaanxi	0	2.42	1.21	0	11.08	5.54
Sichuan	0	1.44	0.72	0	0	0
Yunnan	0.24	25.89	13.07	0	51.76	25.88
Chongqing	0	0	0	15.53	23.20	19.37
Xinjiang	3.45	0	1.73	0	7.04	3.52
Guangxi	5.11	3.96	4.54	0	12.41	6.21

Meanwhile, this paper divides the data into two groups based on the digital access level comprehensive redundancy ratio and the digital technology R&D capability comprehensive redundancy ratio, with the corresponding mean value as the zero boundary point, as shown in Table 5.

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Table 5. Average redundancy of scientific and technological innovation input in 30 provinces (municipalities and autonomous regions) of China in 2022

Digital access level with comprehensive redundancy	Redundancy ratio≤5.28%	Fujian, Gansu, Hubei, Shandong, Shaanxi, Sichuan, Xinjiang, Guangxi
	Redundancy ratio>5.28%	Guizhou, Hainan, Heilongjiang, Hunan, Jilin, Liaoning, Shanxi, Yunnan,
Comprehensive redundancy of digital technology R&D capabilities	Redundancy ratio≤12.98%	Fujian, Heilongjiang, Xinjiang, Hunan, Jilin, Shandong, Shanxi, Shaanxi, Guangxi
	Redundancy ratio> 12.98%	Gansu, Guizhou, Hainan, Hubei, Liaoning, Yunnan, Chongqing

5. Conclusion and Recommendations

5.1. Conclusion

The evaluation results of technological innovation efficiency are significantly influenced by the evaluation index system and model. Based on the understanding that efficiency is the ratio of output to input, the measurement indicators for technological innovation input are mainly set from two aspects: the digital access level of digital capital and the R&D capability of digital technology. Technological innovation output, on the other hand, considers both knowledge and technology output as well as the value of new products. The combination of input and output indicators draws on the availability of data from the 2022 China Statistical Yearbook, the 2022 Annual Statistics of Software and Information Technology Services, the 2022 Intellectual Property Statistical Annual Report, and the 2022 China Science and Technology Statistical Yearbook, selecting measurable indicators.

Against the backdrop of rapidly increasing investment in scientific and technological innovation in China, this study utilizes 2022 data on innovation input-output ratios from 30 provincial-level regions. Through the DEA-BCC model, a static evaluation and comparison of innovation efficiency across these regions was conducted. The analysis reveals that only about one-third of the regions achieved a comprehensive innovation efficiency of 1, still far from the 50% threshold. This indicates that China's overall innovation efficiency remains significantly room for improvement.

From the comprehensive redundancy analysis of digital access levels and digital technology R&D capabilities across provinces, municipalities, and autonomous regions, China's overall digital technology R&D capacity demonstrates higher comprehensive redundancy than its digital access infrastructure. Specifically, these regions can be categorized into five groups: 13 regions including Anhui, Beijing, Tianjin, Shanghai, Jiangsu, and Zhejiang are classified as zero redundancy areas, while Sichuan, Shandong, Xinjiang, Shaanxi, and Fujian form dual-low redundancy regions, indicating high efficiency in digital capital utilization. Liaoning, Guizhou, Yunnan, and Hainan belong to dual-high redundancy regions with significant potential for efficiency improvement. Guangxi, Hunan, Shanxi, Fujian, Jilin, and Heilongjiang are high digital access comprehensive redundancy regions with low digital technology R&D capacity, requiring increased investment in R&D funding and personnel. Gansu, Hubei, and Chongqing represent high digital technology R&D comprehensive redundancy regions with low digital access infrastructure, necessitating strengthened development of internet and digital infrastructure to provide a solid foundation for local technological innovation.

Analysis of comprehensive redundancy metrics for digital access infrastructure and R&D capabilities reveals that, apart from 13 zero-redundancy regions including Beijing, Tianjin, and Anhui, all 17 other provincial-level regions in China exhibit varying degrees of redundancy in both digital connectivity and technological innovation. To address this, relevant authorities should implement tailored innovation support policies based on regional characteristics to

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genuinely enhance scientific and technological innovation efficiency. From a macro perspective, there remains substantial room for improvement in innovation efficiency, with R&D capacity redundancy exceeding digital infrastructure redundancy. However, merely expanding digital infrastructure in these regions may not necessarily boost technological output. Only through comprehensive measures-such as activating the potential of scientific talent and optimizing the allocation of existing capital resources-can we effectively improve and refine innovation efficiency.

5.2. Recommendations

In order to improve the efficiency of regional science and technology innovation and strengthen the supporting role of science and technology innovation in regional economic development, the following suggestions are put forward according to the analysis results of this paper:

(1) Regional level. Areas with strong digital R&D capabilities but low digital infrastructure penetration should prioritize accelerating digital infrastructure development. Key initiatives include coordinated deployment of 5G networks and gigabit networks, large-scale adoption of IPv6, comprehensive advancement of mobile IoT, and widespread implementation of the BeiDou Navigation System. Through multi-channel collaborative growth, innovation investments should be increased to create more opportunities and platforms for scientific innovators. Simultaneously, it is crucial to improve the management and oversight of digital R&D funding, enhancing the efficiency of technological capital and R&D personnel investments. For redundant R&D budgets and personnel, incentive measures should be implemented by expanding research projects and innovation programs, allocating targeted funding for specific R&D topics, and actively guiding researchers to focus on original and forward-looking fundamental research.

For regions with high digital infrastructure access and low R&D capacity in digital technology, greater investment in R&D funding and high-caliber professionals is essential. Existing budgets should be strategically allocated to stimulate innovation, including establishing talent incentive programs such as leadership support initiatives and specialized projects. Researchers may also be granted equity and profit-sharing opportunities in technology development and commercialization. For regions with both high infrastructure access and low R&D capacity, provincial-level governments should align digital infrastructure design with technological innovation capabilities based on local conditions. This requires enhanced coordination of R&D project planning and talent development strategies, optimized allocation of digital capital resources, and ultimately improved overall innovation efficiency.

(2) National Level. First, the government needs to reform its science and technology management policies. Specific measures include: ①Government departments should shift from managing R&D investment to enhancing innovation efficiency. ②Foster a policy environment conducive to scientific innovation, address the overcapacity of R&D personnel and resources in China, and strengthen incentive mechanisms for researchers. ③Optimize resource allocation for innovation to maintain high efficiency. Second, improve innovation allocation methods. Regional innovation efficiency depends not on direct resource expansion, but on optimizing existing resources. The national level should focus on effectively allocating scientific talent, funding, and digital infrastructure, motivate R&D personnel, and ensure rational distribution of research budgets and equipment to avoid redundant or insufficient investments.

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