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A Study on the Measurement and Temporal Evolution of Allocation Efficiency of Science and Technology Innovation Resources: Empirical Evidence from Shandong Province

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Abstract: Against the strategic backdrop of high-quality development and coordinated regional innovation, the allocation efficiency of science and technology (S&T) innovation resources has emerged as a critical performance metric for regional innovation systems. As one of China's leading economic and manufacturing provinces, Shandong possesses a robust foundation in S&T infrastructure and innovation platform development. However, it is currently transitioning from a resource-intensive to an efficiency-oriented paradigm in the allocation of innovation resources. This study employs the Super-Efficiency Slack-Based Measure (Super-SBM) model to assess static allocation efficiency and applies the DEA-Malmquist productivity index to examine dynamic efficiency evolution over time. Empirical findings indicate a sustained upward trend in the overall allocation efficiency of S&T innovation resources across Shandong Province; nevertheless, pronounced inter-regional disparities persist. Several cities exhibit disproportionately high input levels without commensurate output gains, and the marginal returns to resource agglomeration demonstrate significant spatial heterogeneity. To address these challenges, this study proposes a systematic optimization framework anchored in the tripartite principle of "core-driven growth—diffusion-led spillover—regionally coordinated development." Specifically, it advocates establishing a collaborative governance architecture characterized by resource integration, tiered functional specialization, and spatially balanced configuration, while enhancing the adaptability and responsiveness of resource allocation through a dynamic, feedback-informed institutional mechanism.

Keywords: Science and Technology Innovation Resources; Allocation Efficiency; Regional Coordination; Dynamic Governance

1. Introduction

1.1 Research Background

Leveraging scientific and technological progress to improve economic output efficiency, optimize industrial structure and transform the pattern of economic growth has become a core component of national strategy. Achieving the efficient allocation of science, technology and innovation resources at a higher level, across a broader scope and with an optimized structure represents a key current policy objective, while resources constitute the fundamental basis for value creation. In the current stage of innovation-driven development, where new productive forces serve as the core driver, the traditional linear allocation model for S&T innovation resources is increasingly insufficient for the demands of innovation practice, which involve multiple actors, multidimensional factor interactions, and scenario integration. The uncertainty of technological evolution, the systemic complexity of innovation activities, and the dynamic adjustments of policy environments necessitate a shift in resource allocation from static balance to dynamic optimization, and from linear input to system coupling. Therefore, alongside sustained growth in S&T investment, enhancing the efficiency, flexibility, and foresight of resource allocation is not only essential for achieving the national goal of high-level scientific and technological self-reliance and strength, but also a critical breakthrough for regions aiming to improve innovation competitiveness and sustainable development capacity.

As an important base for manufacturing and technological innovation in China, Province Shandong has been designated as a pioneer area for ecological protection and high-quality development in the Yellow River Basin, as well as for green, low-carbon, high-quality development. It also serves as both a key "East Data, West Computing" marine node and a national computing power hub, thereby undertaking dual strategic functions. Shandong Province stands at a pivotal juncture in its innovation development trajectory—transitioning from a "resource-abundant province" defined by aggregate endowments to an "efficiency-oriented province" distinguished by high-value utilization of scientific and technological (S&T) resources. The allocation efficiency of these resources is not only instrumental to the province's sustainable development but also exerts substantial influence on the coherence, balance, and systemic resilience of China's national innovation system.

In recent years, Shandong has consistently expanded its S&T investment and advanced the institutional refinement of its innovation ecosystem. Nevertheless, persistent challenges—including pronounced inter-regional disparities in resource absorption capacity, suboptimal allocation across sectors and institutions, and temporal volatility in efficiency gains—continue to constrain holistic performance. Accordingly, rigorous, evidence-based analysis of the evolutionary dynamics, spatial heterogeneity, and context-sensitive optimization pathways for S&T resource allocation efficiency in Shandong holds considerable theoretical and policy relevance.

1.2 Literature Review and Research Increment

Technological innovation constitutes the principal driver of high-quality development; correspondingly, resource allocation functions as the foundational institutional mechanism that ensures the coherence, efficiency, and adaptive capacity of this driver. As a central tenet in economic theory, resource allocation seeks to optimize the deployment of scarce inputs under conditions of bounded rationality—thereby maximizing societal welfare, productivity growth, and innovation system resilience. Consequently, identifying and mitigating institutional constraints—including ambiguities in property rights assignment, misaligned incentive structures, and fragmented governance frameworks—has become a pivotal theoretical and policy imperative in the optimization of science, technology, and innovation (STI) resources [1]. A robust and growing body of domestic and international scholarship examines STI resource allocation, drawing on heterogeneous conceptual lenses and methodological traditions. This literature coalesces around three interrelated thematic domains:

First, conceptual foundations: definition, taxonomy, and theoretical scope of STI innovation resources.

Technological innovation emerges not from isolated inputs but from the synergistic integration of heterogeneous STI resources; no single component—whether human capital, financial investment, research infrastructure, or digital knowledge assets—can independently sustain systemic innovation performance [2]. STI innovation resources collectively constitute the material, cognitive, and institutional substrate for innovation processes and broader socioeconomic advancement [3]. Core constituents include innovative human capital, R&D funding, advanced physical infrastructure, digital platforms, and high-value informational assets. Accordingly, leading scholars define STI innovation resources as the integrated ensemble of human, financial, physical, informational, and organizational resources that systematically strengthen technological absorptive capacity, adaptive learning, and transformative innovation capability [4]. Innovation resources are characterized by scarcity and the capacity to drive technological progress; as the pace of technological advancement accelerates, the contradiction between insufficient resource supply and surging demand becomes more pronounced [5]. S&T innovation resources are also characterized by strategic importance, scarcity, mobility, regionality, and depreciation. Among these, strategic importance reflects the new connotation of innovation resources and their role in driving economic and social development; scarcity and mobility are inherent properties, regionality reflects spatial distribution characteristics, and depreciation indicates that the effectiveness of resources is limited in time.

Second, the measurement, dynamic evolution, and analysis of allocation efficiency for S&T innovation resources.

Resource allocation studies fall within the realm of economics and, given resource scarcity and rational actor assumptions, the problem of how to maximize resource utility is a key research area, with a critical emphasis on defining the property rights constraints for optimal allocation [6]. To better manage the complex system of S&T innovation resources, it is necessary to distribute and combine all social S&T resources among different actors, disciplines, scientific programs, industry sectors, and spatial-temporal domains, that is, to engage in comprehensive resource allocation activities [7]. Farrell was the first to propose the conceptual framework for efficiency measurement [8], and some experts define S&T resource allocation efficiency as the ratio of various S&T resource inputs—including fiscal, human, and material resources—to the corresponding technological outputs [9]. In the S&T innovation domain, a variety of approaches and model combinations have been used to assess the evolution and spatial distribution of innovation levels in specific regions, with commonly adopted methods including: super-efficiency data envelopment analysis (DEA), GS-SBM model, DEA+CCR model [10], and stochastic frontier analysis (SFA) [11]. Most existing studies construct multi-dimensional, comprehensive evaluation indicator systems [12].

Third, research on influencing factors, governance mechanisms, and optimization strategies.

S&T resources possess both economic and quasi-public goods attributes; thus, they are subject to the basic laws of resource allocation, while also exhibiting partial non-competitiveness and non-excludability. As a result, both market mechanisms and government regulation must be considered in the allocation of S&T resources. Leoncini [13] and Ekboir [14] have highlighted the role of science and technology policy in this process, while factors such as patent data and the stock market's response to patent information also exert certain influences. The bioaccumulation of S&T resource elements must maintain an ecological balance to ensure the breakthrough effect of integrated innovation in research projects. In summary, regional innovation factors such as population, society, and economy, as well as systemic structures—institutions, actors, factors, and networked collaborative innovation—are all significant influences .

Overall, most existing studies focus on the inter-provincial or national scale, with insufficient systematic measurement and dynamic assessment at the intra-provincial city level. These studies also emphasize static efficiency measurement, lacking a comprehensive evaluation that integrates both static (cross-sectional) and dynamic (temporal) perspectives—namely, a dual approach combining "static and dynamic" tests. Additionally, studies that identify resource allocation types based on measurement results and deduce governance strategies are relatively scarce. In response, this paper's literature positioning and contributions are mainly reflected in the following aspects: Methodologically, it constructs a dual-assessment framework based on "super-efficiency EBM (static ranking) + Malmquist (dynamic decomposition)," enhancing both the discriminatory power and temporal explanatory capacity of efficiency identification. In terms of geographical scope, this study centers on the 16 prefecture-level cities of Shandong Province, enabling a controlled comparative analysis of the spatial heterogeneity and longitudinal evolution patterns in science, technology, and innovation (STI) resource allocation—thereby isolating institutional and market commonalities while illuminating city-specific efficiency differentials.

2. Research Methodology and Framework Design

2.1 Research Methodology

2.1.1 Super-efficient EBM model

There are various methods for measuring the efficiency of S&T resource allocation, which can essentially be categorized into two main types: non-parametric and parametric approaches. The representative non-parametric method is Data Envelopment Analysis (DEA), which was first proposed by Charnes et al. as a non-parametric approach for evaluating a set of homogeneous decision-making units (DMUs) with multiple inputs and outputs. Due to the fact that DEA does not require a pre-specified production function and can objectively reflect

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the real situation of complex S&T innovation systems with multiple inputs and outputs, it has been widely applied in efficiency measurement across various fields. By establishing a relative efficiency evaluation system based on the best-practice frontier, DEA enables horizontal comparison of S&T resource input and output across different regions or units, revealing relative efficiency levels, redundancy, and optimization potential. In recent years, the optimal allocation of innovation resources has become an important measure to enhance indigenous innovation capabilities and deepen reform of the S&T system, making DEA especially applicable in the context of S&T resource allocation.

The primary representative of parametric methods is the Stochastic Frontier Analysis (SFA) approach. SFA estimates the technical efficiency of S&T resource inputs and outputs, as well as the impact of random factors on the production process, by specifying a particular production function and employing econometric models. Compared to the non-parametric characteristics of DEA, parametric approaches offer more explicit functional forms and assumptions, enabling robust statistical inference and analysis of influencing factors. However, their main limitation is sensitivity to the specification of the functional form. Additionally, DEA models typically analyze production technology within a single period and cannot capture changes in efficiency of different DMUs over time, thus providing only static analysis and failing to reflect the dynamic evolution of S&T resource allocation efficiency. Another issue with DEA is that, in the generalized reference set approach, the evaluation reference system in traditional DEA is composed of only efficient DMUs, meaning that only comparisons with efficient units are possible. In practice, however, it is often necessary to compare with other reference samples beyond just the "efficient units." Thus, the concept of a "sample possibility set" coexists with the "production possibility set," and varying the selection of the sample set leads to different frontier surfaces and, consequently, to evaluation results greater than one. The improved DEA model, known as the super-efficiency DEA model, enables further distinction among efficient DMUs and thus supports more nuanced performance ranking.

Both radial and non-radial models in DEA have their own limitations. The Epsilon-Based Measure (EBM) super-efficiency model, proposed by Tone et al. [15], relaxes the assumption of proportional reduction in input factors in radial models, effectively combining radial and non-radial methods. This allows compatibility between the radial proportion of frontier and actual input values and the non-radial slack in differentiated input reduction, thus effectively addressing the shortcomings of the CCR (radial) and SBM (non-radial) models. Therefore, this study adopts the EBM model as the foundation, incorporating super-efficiency and non-oriented measurement, to assess the efficiency of S&T resource allocation in Shandong Province. The specific linear programming formulation is as follows:

$$r^* = \min \frac{\theta - \varepsilon_x \sum_{i=1}^{m} \frac{\varpi_i^- s_i^-}{x_{i0}}}{\varphi + \varepsilon_y \sum_{r=1}^{s} \frac{\varpi_r^+ s_r^+}{y_{r0}}} \tag{1}$$

$$\text{s.t.} \begin{cases} \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{i0} (i = 1, 2, \cdots, m) \\ \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \varphi y_{r0} (r = 1, 2, \cdots, s) \\ \lambda_j \geq 0, \sum \lambda = 1 \\ s_i^- \geq 0, s_r^+ \geq 0 \end{cases} \tag{2}$$

In Equations (1) and (2), r^* represents the comprehensive efficiency score; n denotes the number of Decision Making Units (DMUs); x and y refer to input and desirable output variables, respectively; m and s indicate the number of inputs and desirable outputs; λ represents the relative importance of reference units; α and β are the programming parameters for the radial part; s_i^- sand s_r^+ denote the slack variables for the i-th input and the r-th desirable output, respectively; ϖ_i^- and ϖ_r^+ represent the weights for the i-th input and the r-th desirable output, respectively; ε is the parameter representing the importance of the non-radial component in the super-efficiency EBM model, with a value range of [0, 1].

2.1.2 Malmquist index

This study introduces the Malmquist Total Factor Productivity (TFP) index model to dynamically capture intertemporal trends in efficiency and to distinguish between different sources of efficiency variation, such as technological progress, pure technical efficiency, and scale efficiency. This approach provides an objective basis for the continuous improvement of S&T innovation resource allocation. The concept of the Malmquist index was originally introduced by Malmquist in the analysis of the consumption sector and has since been extended by numerous scholars [16], achieving wide application in econometrics. By measuring the distance between the actual production of each decision-making unit and the best-practice frontier, the dynamic changes in the Malmquist index can be calculated [17]. The Malmquist index effectively compensates for the limitations of the DEA model by analyzing changes in total factor productivity (TFP) and quantifying the contribution of technical efficiency, technological progress, pure technical efficiency, and scale efficiency to TFP. This belongs to the domain of dynamic analysis.

The Malmquist index can be decomposed into two components: (1) changes in technical efficiency between two periods (Technical Efficiency Change, TEC); and (2) changes in production technology (Technological Change, TC), which in the context of DEA is reflected in the shift of the production frontier.

The Malmquist index from period t to t+1 is expressed as follows:

$$MI\left(x_K^{t+1},y_K^{t+1},x_K^t,y_K^t\right)=\sqrt{\frac{E^t(x_K^{t+1},y_K^{t+1})E^{t+1}(x_K^{t+1},y_K^{t+1})}{E^t(x_K^t,y_K^t)E^{t+1}(x_K^t,y_K^t)}} \tag{3}$$

In Equation (3), E^x(for the current unit under evaluation) represents the efficiency value derived from the DEA model. $E^t(x_K^{t+1},y_K^{t+1})$ denotes the efficiency value of decision-making unit K in period t+1, calculated using the data of all DMUs in period t as the reference set (efficient frontier). The meanings of the other symbols follow the same logic.

$E^t(x_K^t,y_K^t)$ and $E^{t+1}(x_K^t,y_K^t)$ represent the technical efficiency values of decision-making unit K in periods t and t+1, respectively. TEC (Technical Efficiency Change) refers to the change in technical efficiency between the two periods, as shown in Equation (4):

$$TEC=\frac{E^{t+1}(x_K^{t+1},y_K^{t+1})}{E^t(x_K^t,y_K^t)} \tag{4}$$

The technological change (TC) from period t to t+1 (i.e., the shift of the production frontier) can be expressed as Equation (5):

$$TC=\sqrt{\frac{E^t(x_K^t,y_K^t)E^t(x_K^{t+1},y_K^{t+1})}{E^{t+1}(x_K^t,y_K^t)E^{t+1}(x_K^{t+1},y_K^{t+1})}} \tag{5}$$

Thus, the Malmquist index can be decomposed into two components: Technical Efficiency Change (TEC) and Technological Change (TC). In Equation (6), the comprehensive technical efficiency change index (TEC) can be further decomposed into the product of the pure technical efficiency change index (PEC) and the scale efficiency change index (SEC), that is, TEC = PEC × SEC. Therefore, MI = TEC × TC = PEC × SEC × TC.

$$\begin{aligned}MI\left(x_K^{t+1},y_K^{t+1},x_K^t,y_K^t\right)&=\sqrt{\frac{E^t(x_K^{t+1},y_K^{t+1})E^{t+1}(x_K^{t+1},y_K^{t+1})}{E^t(x_K^t,y_K^t)E^{t+1}(x_K^t,y_K^t)}}\\&=\frac{E^{t+1}(x_K^{t+1},y_K^{t+1})}{E^t(x_K^t,y_K^t)}\sqrt{\frac{E^t(x_K^t,y_K^t)E^t(x_K^{t+1},y_K^{t+1})}{E^{t+1}(x_K^t,y_K^t)E^{t+1}(x_K^{t+1},y_K^{t+1})}}\\&=TEC*TC\end{aligned} \tag{6}$$

Based on the need to analyze the temporal evolution and spatial heterogeneity of regional S&T resource allocation efficiency in Province S, this study adopts the non-parametric EBM-Malmquist productivity index method as the core measurement tool. This method is especially suitable for multidimensional and multi-regional longitudinal and cross-sectional comparisons, with strong computational operability. It further reveals the spatiotemporal evolution patterns and paths of S&T innovation resource allocation efficiency.

2.2 Framework Design

2.2.1 Indicator system

The improvement of regional innovation performance, the stimulation of corporate innovation vitality, and the upgrading of industrial innovation—all supported and driven by the allocation of S&T innovation resources—are complex issues involving the input of multiple types of S&T resources and resulting from multiple concurrent causal mechanisms. Moreover, this study aims to explore the temporal evolution characteristics of S&T innovation resource allocation efficiency. Therefore, in accordance with the new requirements for innovation resources under innovation-driven development, and with reference to existing innovation resource indicators such as those in the China Regional Innovation Capability Evaluation Report and the National Innovative Cities Innovation Capability Evaluation Report, this study follows the principles of scientific rigor, relevance, and data availability. Based on the perspectives of "S&T resource input" and "S&T resource output," a comprehensive evaluation indicator system is constructed, with all selected indicators being positive indicators.

Table 1. Indicator System for the Efficiency of Resource Allocation

Primary Indicator	Secondary Indicator	Tertiary Indicator
S&T Resource Input	Input of S&T Human Resources	Full-time equivalent of R&D personnel (persons/year)
	Input of S&T Financial Resources	Investment in S&T fixed assets (10,000 CNY)
	Input of S&T Physical Resources	Investment in S&T fixed assets (10,000 CNY)
S&T Resource Output	Output of S&T Activities	Annual number of granted patents (items)
	Commercialization of S&T Achievements	Annual transaction volume in technology market (100 million CNY)

As shown in Table 1, the primary indicators include S&T Resource Input and S&T Resource Output. Among these, S&T Resource Input is primarily divided into input in human, financial, and physical resources. S&T Resource Output is based on the principle of reflecting the value created and the effects generated, with the indicators being output of S&T activities and commercialization of S&T achievements.

S&T human resource input is the foundation of technological innovation activities and the key to sustaining innovation and development in the region, measured by the full-time equivalent of R&D personnel. S&T financial resource input represents the region's financial support for technological activities, and is measured by R&D expenditure, reflecting the actual use and investment in technological activities. S&T physical resource input provides the necessary conditions for the smooth implementation of technological innovation activities, measured by social fixed asset investment, specifically the data for scientific research and technical services under the 13th classification of industry. When calculating for the 16 cities in Shandong Province, more basic data on social fixed asset investment is used.

S&T Resource Output includes two aspects: direct output (knowledge) and indirect output (economic impact). Direct technical innovation is measured by the number of domestic patent applications accepted. Indirect economic output refers to the market conversion of technological innovation, primarily measured by the annual transaction volume in the technology market. Since all the selected indicators are positive indicators, non-desirable outputs, such as industrial wastewater discharge, total industrial air emissions, and industrial solid waste generation, are excluded from consideration in measuring S&T resource output.

It is also important to note that there is a certain time lag between S&T Resource Input and S&T Resource Output. Typically, lag variables are chosen from 1 to 3 periods. For the data on technological innovation input and output, this study sets the lag period for S&T Resource Output as one year, meaning that the original input-output data set (X_i, Y_i) is modified to (X_i, Y_{i+1}) and then used in the model for calculation. This means that the efficiency of S&T innovation resource allocation in year i is derived from the input in year i-1 and the output in year i. This indicator system not only covers traditional dimensions of S&T input and output but also integrates the degree of market application of regional innovation achievements, thus providing a more accurate reflection of the efficiency and output quality of regional S&T resource allocation.

2.2.2 The time dimension and spatial scale

In terms of the temporal dimension, this study selects the period from 2019 to 2023 as the analysis cycle, based on the following three considerations: First, this period represents a key phase for Shandong Province in deepening reforms in its science and technology system and promoting the innovation-driven development strategy. It covers the later stages of the 13th Five-Year Plan and the early to mid stages of the 14th Five-Year Plan, reflecting both the historical process of policy transformation and the early signs of reform outcomes. Second, since 2018, Shandong province has accelerated the transformation of old and new growth drivers, pushing the transformation of traditional industries and optimizing the layout of emerging strategic industries. Both the scale and structure of S&T investment have undergone significant changes, driving a reallocation of innovation resources. Lastly, the fourth national economic census conducted in 2018 unified the GDP accounting system across regions, improving the data's authority and comparability. Accordingly, since 2019, technological statistics have exhibited enhanced continuity, consistency, and temporal stability—particularly under prevailing institutional constraints—thereby improving their reliability and validity for tracking the longitudinal evolution of regional science, technology, and innovation (STI) resource allocation efficiency.

At the sub-provincial spatial scale, this study encompasses all 16 prefecture-level cities of Shandong Province—including the two sub-provincial municipalities of Jinan and Qingdao—and deliberately selects a stratified sample of representative cities (e.g., Yantai, Weifang, Linyi, and Dezhou) that exhibit systematic variation across three critical dimensions: industrial composition, geographical positioning, and developmental trajectory.These cities are located in the three major regional economic zones: the Jiaodong Economic Circle, the Capital Economic Circle, and the Lunan Economic Circle. This geographically comprehensive coverage ensures robust spatial representativeness and meaningful heterogeneity, thereby enabling rigorous identification of both structural disparities and dynamic evolutionary trajectories in science, technology, and innovation (STI) resource allocation efficiency across sub-provincial units. It further supports a systematic elucidation of the functional mechanisms underpinning Shandong's provincial innovation ecosystem. By systematically comparing cities differentiated by administrative tier, developmental stage, and economic profile, the study advances nuanced understanding of regional technological development—particularly with respect to equilibrium maintenance, cross-scale coordination, and gradient-driven transformation. These insights provide an empirically grounded foundation for designing tiered, context-sensitive, and functionally aligned STI resource allocation strategies.

It is worth noting that the output data for 2020 correspond to the input data for 2019. Therefore, the input data used in the analysis are from 2019 to 2022, while the output results correspond to the period from 2020 to 2023.

3. Time-Domain Evolution of Resource Allocation Efficiency in Shandong's Scientific and Technological Innovation

3.1 Static Evaluation

Based on the Maxdea 9Ultra platform, the super-efficiency EBM model is used to measure the S&T resource allocation efficiency of each city in Shandong Province from 2020 to 2023, with the results shown in Table 2. Between 2020 and 2023, the average efficiency of S&T resource allocation in Shandong Province ranged from 0.700 to 0.761, indicating that there is still more than a 20% potential for improvement in overall efficiency. In terms of individual cities, only Heze and Jinan reached an efficient level of resource allocation efficiency on average during the study period. Moreover, only Qingdao, Weifang, and Binzhou had average efficiency values above 0.8, while the other 11 cities had average efficiency values below 0.8. Among them, Tai'an had the lowest efficiency value. The overall efficiency of S&T resource allocation across cities in Shandong Province shows significant disparity, with too few high-efficiency cities and a pronounced regional imbalance in efficiency.

A further analysis of the S&T resource allocation efficiency and its decomposition across cities in Shandong Province for 2023 in Table 3, reveals that the comprehensive efficiency of S&T resource allocation in the province has an average value of 0.756. The average values for pure technical efficiency and scale efficiency are 0.859 and 0.888, respectively, indicating that, overall, scale efficiency slightly exceeds pure technical efficiency. In 2023, only Jinan, Qingdao, and Heze achieved a comprehensive efficiency above 1. However, the efficiency levels of other cities are relatively low, all below 0.8, with significant regional disparities. For instance, Rizhao had a particularly low efficiency, at only 0.446. Jinan, Qingdao, Zaozhuang, Yantai, and Heze all achieved efficient S&T resource allocation, while other cities need to further improve their management and technical levels of S&T innovation resource allocation.

Table 2. Efficiency of Science and Technology Resource Allocation in Various Cities

Cities	2020	2021	2022	2023	Mean
Jinan	1.045	1.077	1.067	1.050	1.060
Qingdao	0.628	0.604	1.000	1.036	0.817
Zibo	0.742	0.883	0.693	0.677	0.749
Zaozhuang	0.617	0.766	1.003	0.725	0.778

Dongying	0.377	0.605	0.601	0.674	0.564
Yantai	0.446	0.490	0.569	0.654	0.540
Weifang	1.000	0.817	0.704	0.709	0.808
Jining	0.609	0.581	0.660	0.859	0.677
Taian	0.359	0.440	0.648	0.603	0.512
Weihai	0.511	0.583	0.522	0.689	0.576
Rizhao	0.632	0.617	0.533	0.446	0.557
Linyi	0.589	0.533	0.527	0.591	0.560
Dezhou	0.489	0.603	0.829	0.688	0.652
Liaocheng	0.747	0.798	0.839	0.750	0.783
Binzhou	1.051	1.164	0.678	0.740	0.908
Hezao	1.356	1.258	1.304	1.210	1.282
Mean	0.700	0.739	0.761	0.756	0.739

Regarding scale efficiency, most cities have relatively high efficiency levels, with only Zaozhuang, Yantai, and Rizhao having values below 0.7. The efficiency scores for the remaining fourteen cities all exceed 0.9, reflecting a generally high level of allocative performance in science, technology, and innovation (STI) resource utilization. With respect to returns to scale (RTS), ten cities—including Zaozhuang and Rizhao—operate under increasing returns to scale, indicating that marginal productivity gains can be realized through moderate expansion of input volume. Conversely, the six remaining cities exhibit decreasing returns to scale, implying diminishing marginal returns to additional inputs; for these jurisdictions, optimizing scale efficiency necessitates strategic recalibration—particularly a reduction in input intensity—rather than further resource expansion.

Table 3. Efficiency of Science and Technology Resource Allocation and Its Decomposition by Various Cities

Cities	Overall Efficiency	Pure Technical Efficiency	Scale Efficiency	Returns to Scale
Jinan	1.050	1.054	0.997	Increasing
Qingdao	1.036	1.179	0.878	Decreasing
Zibo	0.677	0.686	0.988	Decreasing
Zaozhuang	0.725	1.143	0.634	Increasing
Dongying	0.674	0.710	0.949	Increasing
Yantai	0.654	1.044	0.626	Decreasing
Weifang	0.709	0.815	0.870	Decreasing
Jining	0.859	0.866	0.992	Decreasing
Taian	0.603	0.653	0.923	Increasing
Weihai	0.689	0.697	0.988	Increasing
Rizhao	0.446	0.682	0.654	Increasing
Linyi	0.591	0.649	0.911	Decreasing
Dezhou	0.688	0.705	0.976	Increasing
Liaocheng	0.750	0.823	0.912	Increasing
Binzhou	0.740	0.783	0.945	Increasing
Hezao	1.210	1.254	0.965	Increasing
Mean	0.756	0.859	0.888	

Note: Constant indicates constant returns to scale, decreasing indicates decreasing returns to scale, and increasing indicates increasing returns to scale.

3.2 Dynamic Index Analysis

Based on the global reference Malmquist index method, this study further analyzes the total factor productivity (TFP) index of S&T resource allocation and its decomposition for each city in Shandong Province from 2020 to 2023. As shown in Table 4, the average TFP index for Shandong Province from 2020 to 2023 is 0.973, indicating an average annual decline of 2.7% in the total factor productivity of S&T resource allocation. The TFP index was above 1 only in 2020-2021, and it saw significant declines in the 2021-2023 period. In terms of index decomposition, the average annual technological progress index is 0.936, indicating a 6.4% annual decline in the technological level of S&T resource allocation. While the technological progress index reached

1.187 in 2020-2021, showing an 18.7% increase, it sharply dropped in 2021-2023. The average annual pure technical efficiency change index and scale efficiency change index were 1.015 and 1.024, respectively, showing a slight improvement. From the annual perspective, the overall fluctuation in technological development management and resource allocation levels is relatively small. It can be observed that the main reason for the decline in the efficiency of S&T resource allocation in Shandong Province, especially the significant decline between 2021 and 2023, is the substantial decrease in technological levels.

Table 4. Total Factor Productivity Index and Its Decomposition

Year	TFP Index	Pure Technical Efficiency Change Index	Scale Efficiency Change Index	Technological Progress Index	Comprehensive Technical Efficiency Change Index
2020-2021	1.281	1.047	1.030	1.187	1.079
2021-2022	0.831	1.006	1.034	0.799	1.040
2022-2023	0.866	0.994	1.009	0.863	1.003
Mean	0.973	1.015	1.024	0.936	1.040

Table 5 Total Factor Productivity Index and Its Decomposition for Various Cities

Cities	TFP Index	Pure Technical Efficiency Change Index	Scale Efficiency Change Index	Technological Progress Index	Comprehensive Technical Efficiency Change Index
Jinan	0.934	1.000	1.002	0.932	1.002
Qingdao	0.986	1.006	1.175	0.834	1.181
Zibo	0.955	0.972	0.998	0.984	0.970
Zaozhuang	0.943	1.033	1.022	0.894	1.056
Dongying	1.168	1.224	0.992	0.963	1.214
Yantai	1.001	1.004	1.131	0.881	1.136
Weifang	0.891	0.911	0.979	1.000	0.892
Jining	0.993	0.991	1.131	0.885	1.121
Taian	1.117	1.208	0.984	0.939	1.189
Weihai	1.032	1.068	1.034	0.934	1.104
Rizhao	0.836	0.982	0.907	0.939	0.890
Linyi	0.918	0.967	1.035	0.917	1.001
Dezhou	1.039	1.107	1.013	0.927	1.121
Liaocheng	0.929	0.962	1.041	0.928	1.001
Binzhou	0.885	0.905	0.983	0.995	0.890
Hezao	1.001	0.965	0.998	1.040	0.963
Mean	0.973	1.015	1.024	0.936	1.040

From Table 5, which shows the TFP index and its decomposition for each city, it can be observed that only six cities—Dongying, Yantai, Tai'an, Weihai, Dezhou, and Heze—had an average annual TFP index above 1.1, with Dongying and Tai'an having average annual TFP indices above 1.1. The high pure technical efficiency change index is the main reason driving the efficiency improvement in Dongying and Tai'an. In contrast, the other 10 cities experienced varying degrees of decline in the TFP index for S&T resource allocation. Among these, Weifang, Rizhao, and Binzhou had an average annual TFP index below 0.9. The decline in efficiency in Weifang and Binzhou was mainly due to low pure technical efficiency change indices, while Rizhao’s decline was primarily attributed to a low scale efficiency change index. It is worth noting that only Heze had a technological progress index above 1, whereas other cities failed to achieve an increase in S&T resource allocation efficiency through technological progress. Moreover, the differences in the pure technical efficiency change index and the scale efficiency change index between cities are significant, indicating that local technological innovation should focus on strengthening technological capabilities, while also promoting improvements in management and resource allocation capabilities in certain cities to enhance overall S&T resource allocation efficiency.

3.3 Spatial distribution of science and technology innovation resource allocation

Based on the Malmquist index measurement and dynamic evaluation of the efficiency of science and technology innovation resource allocation across 16 cities in Shandong Province from 2020 to 2023, this study identifies significant spatial heterogeneity in resource allocation efficiency at the provincial scale. This spatial pattern manifests both in cross-sectional disparities of efficiency levels across cities within any given year and in the spatiotemporal dynamics of efficiency change—including geographic agglomeration, diffusion gradients, and regional divergence—over the study period.

Overall, the efficiency of science, technology, and innovation (STI) resource allocation in Shandong Province displays a pronounced east–west spatial gradient—characterized by higher efficiency in eastern cities—and a secondary north–south asymmetry, with southern cities outperforming their northern counterparts. Coastal and core metropolitan centers—including Qingdao, Jinan, and Weifang—sustained high and stable levels of both overall technical efficiency (OTE) and pure technical efficiency (PTE) throughout the study period, thereby qualifying as "high-performing and structurally resilient" regions. These jurisdictions benefit from systemic advantages across multiple dimensions: large-scale economic agglomeration, advanced research infrastructure, concentrated higher education institutions, and deep pools of innovative human capital—collectively positioning them as primary engines of STI resource optimization and pivotal nodes for innovation spillovers across the province. Illustratively, Qingdao maintained consistently high DEA efficiency scores over the four-year observation window, while its Malmquist productivity index exhibited sustained positive growth—indicating continuous improvements in both allocative efficiency and technological progress, alongside robust input utilization.

In contrast, cities in western and southern Shandong—including Liaocheng, Heze, and Zaozhuang—consistently register lower STI resource allocation efficiency scores. In several years, their scores fall substantially below the DEA-derived efficient frontier, signaling systemic inefficiencies: notably, input overutilization (e.g., underutilized R&D funding or idle research infrastructure) and output shortfalls (e.g., low patent commercialization rates or limited high-tech firm formation). These performance gaps stem from structural constraints: relatively underdeveloped industrial ecosystems, scarcity of national- or provincial-level innovation platforms (e.g., key laboratories, technology transfer centers), and persistent deficits in high-caliber innovative talent—factors that collectively impede the formation of robust resource aggregation mechanisms and closed-loop resource recycling systems. Consequently, these jurisdictions constitute priority "structural transformation" zones—requiring not only targeted fiscal and institutional support but also externally anchored capacity-building interventions, such as inter-city innovation partnerships and platform-sharing arrangements.

From a spatial evolutionary perspective, urban agglomerations—including the provincial capital metropolitan area (Jinan) and the Jiaodong Economic Circle—demonstrate significantly higher STI resource allocation efficiency compared to southwestern Shandong. Notably, longitudinal analysis of the Malmquist productivity index reveals strong intra-regional coordination and convergence in technical efficiency and technological progress across Jiaodong cities. By contrast, western and southern Shandong exhibit greater volatility in efficiency trajectories, with divergent and non-synchronized temporal patterns—indicating fragmented development dynamics and weak inter-city spillover linkages. Collectively, these patterns suggest that a functionally integrated, cross-regional STI resource allocation network remains underdeveloped; persistent spatial stratification risks reinforcing path dependence, wherein leading regions consolidate advantages through cumulative causation, while lagging areas face structural inertia and diminishing returns to incremental investment.In addition, the spatial analysis conducted in this study reveals an evolutionary tendency toward "central polarization followed by secondary diffusion" in the efficiency of science and technology resource allocation in Shandong Province. The provincial capital core represented by Jinan has promoted modest efficiency improvements in neighboring cities such as Tai'an and Dezhou through resource mobilization, policy diffusion, and platform sharing. However, a stable innovation corridor effect has not yet emerged. Meanwhile, eastern cities such as Qingdao and Yantai have followed relatively independent growth trajectories while steadily improving their own efficiency levels, and their spillover effects on surrounding areas remain limited.

Overall, the spatial configuration of science, technology, and innovation (STI) resource allocation efficiency in Shandong Province is undergoing an incipient transition—from a historically dominant single-core agglomeration model centered on Jinan and Qingdao toward an emergent multi-core coordinated development paradigm—yet pronounced spatial disparities persist across sub-provincial units.

4 Optimization Strategies for Science and Technology Innovation Resource Allocation Efficiency in Shandong Province

4.1 Overall Strategy

Science and technology resources constitute an integrated system in which internal elements are closely interconnected. The allocation of science and technology innovation resources is shaped by complex and concurrent configurations of multiple factors. No single condition related to science and technology innovation resources can constitute a sufficient driver of regional revitalization. Instead, the realization of high regional innovation performance, strong enterprise innovation vitality, and advanced industrial innovation upgrading depends on the coordinated alignment of multiple conditions, including science and technology funding, innovation talent, innovation policies, and innovation services.

In addition, the jurisdiction-based management model formed under administrative divisions has intensified the tendency toward homogenization in both industrial structure and the allocation of science and technology innovation resources. In the cultivation of leading industries and the agglomeration of innovation factors, market segmentation and policy discontinuities remain evident, thereby weakening economies of scale and reducing the upgrading capacity of the value chain. The shadow effects and spillover effects generated by large cities are crucial for achieving balanced regional economic development [18]. From the perspective of urban spatial development patterns, the spatial distribution of science and technology innovation resources determines both their spillover effects and allocation performance.

Therefore, on the basis of quantitative analysis and dual validation, and supported by a polycentric collaborative spatial layout, Shandong Province should build a collaborative innovation pattern characterized by interregional complementarity and functional connectivity. It should also establish a systematic optimization framework featuring resource co-accumulation, tiered development, and spatial coordination. This has become a critical pathway for Shandong to optimize the allocation of science and technology resources and promote high-quality industrial development.

4.2 Implementation Pathways

First, Shandong should advance the systematic construction of a tiered, functionally integrated innovation network—anchored by dual core engines (Jinan and Qingdao), reinforced by four secondary innovation centers (Yantai, Weifang, Zibo, and Weihai), and extended through strategically positioned supporting nodes (Heze, Linyi, and Dezhou). This architecture must prioritize strengthening the systemic leadership capacity of Jinan and Qingdao as primary drivers. Specifically, Jinan should be empowered to host national key laboratories and domain-specific innovation platforms in high-end intelligent manufacturing and artificial intelligence, while accelerating the commissioning of major scientific infrastructure projects. Concurrently, Qingdao should intensify its role as an open innovation hub—deepening strategic international partnerships in marine science and technology, intelligent home systems, and advanced functional materials—to consolidate its global competitiveness and knowledge gateway function. At the same time, Jinan and Qingdao should enhance interconnectivity in science and technology resource data and promote the co-construction and sharing of innovation platforms, thereby achieving functional complementarity and resource synergy between the two cores. Then, regional science and technology subcenters should be cultivated at a faster pace. Cities such as Yantai, Weifang, Zibo, and Weihai, which have relatively strong industrial foundations and accumulated technological capabilities, should play a pivotal role in undertaking the transformation of scientific and technological achievements and promoting pilot-scale incubation. Through regional science and technology cooperation mechanisms, a spatial collaboration network linking core cities, subcenters, and node cities should be formed, thereby facilitating the deep integration of innovation chains and industrial chains. Supporting node cities such as Heze, Linyi, and Dezhou should strengthen their local capacity-building through the precise introduction of resources and targeted policy support. These cities should develop high-growth science and technology “enclaves” and industrial incubation bases, so as to enhance their capacity for undertaking, diffusing, and transforming innovation resources.

Second, Shandong should promote the transformation of innovation resource flows from one-way diffusion to two-way interaction and networked collaboration, and establish cross-regional mechanisms for resource sharing and functional coordination. Cross-regional cooperation platforms, industrial-chain collaborative innovation centers, regional joint laboratories, and demonstration bases for industrial application scenarios should be explored. The open mutual recognition and cross-use of research platforms should be promoted to avoid duplicate investment and idle resources. High-quality platforms should be encouraged to extend services to regional innovation actors, thereby improving the accessibility of research facilities for grassroots research organizations. For example, Jinan, Qingdao, Weifang, and Yantai could establish joint innovation centers or industrial alliances focusing on advantageous fields such as next-generation information technology, high-end equipment manufacturing, and biomedicine, thereby sharing talent resources, research facilities, and industrial technologies. Linyi and Heze could also cooperate with Jinan and Qingdao to build cross-regional enclave research institutes or enclave industrial parks, so as to effectively absorb technological spillovers and accelerate the transformation of scientific and technological achievements. Then, the powerful innovation and creativity generated by the spatial agglomeration of science and technology talent should be further activated. The spatial concentration of innovation talent facilitates the flow and transmission of both explicit and tacit knowledge within regions, thereby generating positive externalities from individual innovation agglomeration [19]. Policy barriers between cities and regions should be removed, restrictions on the settlement of innovation talent should be reduced, and the spatial agglomeration of innovation talent should be encouraged. Particular attention should be paid to the concentration of talent in strategic emerging industries that represent the future direction of scientific and technological development. By fully leveraging agglomeration spillovers, Shandong can accelerate the formation of new quality productive forces in key industries. Moreover, the flexible mobility of talent and the construction of interregional collaborative networks should be promoted, with the aim of forming a regional collaborative innovation community centered on talent. The structure of fiscal investment in science and technology across different cities should be optimized in a coordinated manner. Fiscal support should shift from an undifferentiated and broadly distributed model to a more targeted and precision-oriented model. Public science and technology funds should be directed toward original innovation, high-end platforms, and the transformation of scientific and technological achievements. At the same time, enterprises should be encouraged to increase R&D investment, and a composite investment mechanism characterized by government guidance, enterprise leadership, and diversified financing should be established.

Finally, Shandong should improve the multilevel institutional support system for science and technology resource allocation [20]. Institutional supply refers to the process through which decision-makers innovate and establish formal rules through specific procedures and channels under given constraints. Institutional factors play a decisive role in the allocation of science and technology innovation resources. The institutional mechanisms for science and technology innovation resource allocation can promote governmental transformation and regulate and guide the science and technology activities of market-based innovation actors. A science and technology innovation institution can be understood as a set of formal rules designed to respond to, adapt to, or align with science and technology innovation activities and institutional supply. An institutional foundation for collaborative governance should be established [21]. From the perspective of institutional design, an efficient organizational coordination mechanism can be developed through joint conferences on regional collaborative development. Regional cooperation plans for differentiated development should be introduced, and cross-regional policy-sharing mechanisms should be explored, thereby providing institutional guarantees for mutually beneficial regional development. Horizontal collaboration among government, industry, universities, research institutes, and application-oriented actors should be promoted. A coordination committee or joint meeting mechanism for science and technology resource allocation may be established to improve information symmetry and joint decision-making among different actors. Vertically, the linkage mechanism among the provincial, municipal, and county levels should be strengthened, especially in policy implementation, data sharing, and responsibility allocation, so as to ensure policy consistency and efficient execution across administrative levels. The supply of innovation policies should be strengthened. In view of the differences among regions, industries, and innovation actors in Shandong Province, a policy system with a clear structure and well-defined hierarchy should be developed to avoid blind spots caused by one-size-fits-all policy design and to reduce resource waste. A multi-tiered, regionally calibrated, and stakeholder-inclusive policy framework—differentiated by administrative level, territorial function, and institutional mandate—can substantially improve the targeting accuracy and implementation efficacy of public investment in innovation.

5. Conclusions

The 15th Five-Year Plan period constitutes a pivotal phase in China's pursuit of socialist modernization—functioning strategically as a critical transition linking the completion of the first centenary goal with the comprehensive advancement of the second centenary objective. In the face of a complex and challenging domestic and international environment, stable growth should be given priority, with structural adjustment as the main line of policy implementation. Sustained and stable economic growth hinges critically on deepening institutional reforms, accelerating innovation-driven development, and expanding high-standard openness—key levers for unlocking endogenous growth momentum. For Shandong Province, achieving both high-efficiency allocation of science, technology, and innovation (STI) resources and high-quality industrial upgrading requires foundational improvements in governance capacity and systemic optimization of resource allocation institutions. Guided by systems thinking, policy implementation must be grounded in four interdependent principles: differentiation (tailoring instruments to functional zones and administrative tiers), precision (targeting bottlenecks with evidence-based interventions), dynamism (enabling adaptive recalibration in response to evolving innovation trajectories), and coordination (aligning fiscal, regulatory, and spatial planning instruments across jurisdictions). Collectively, these principles underpin a responsive, learning-oriented institutional architecture—one capable of accommodating the fluidity of innovation resource flows and advancing province-wide coordinated development.

However, this study has not comprehensively addressed several frontier research topics, including innovation ecosystem theory, co-evolutionary mechanisms of institutional coordination, and regional innovation capacity resilience. Future research should maintain resource allocation efficiency as the central analytical lens, while strengthening policy-relevant insights grounded in spatial distribution patterns, dynamic governance frameworks, and multi-stakeholder collaborative mechanisms. As technological innovation transitions from factor-driven to system-driven development, subsequent scholarship ought to prioritize systemic coordination logic, coupling pathways among innovation elements, and the hierarchical, nested architecture of institutional networks. Such efforts will advance the development of a theoretically robust and contextually grounded framework for science and technology resource allocation—one that reflects China's institutional realities and aligns with regional development imperatives.

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References

[1] Wei Xinghua, Hou Weimin. Choice of Economic Growth Styles in China and

Transition from the Extensive Style to the Intensive One. Economic Research Journal, 2007, (7): 15-22.
[2] Zhang F, Wang Y, Liu W. Science and Technology Resource Allocation, Spatial Association, and Regional Innovation. Sustainability 2020, 12: 694.
[3] Wang J Q.A Rational Analysis of Regional Science and Technology Innovation Resources and Their Allocation. Science and Technology & Innovation, 2018, (23): 95-96.
[4] Wang X Y, Wang H Q.A DEA Analysis of the Efficiency of Science and Technology Innovation Resource Allocation in China. Statistics & Decision, 2008, (08): 108-110.
[5] Qin Y B, Zhang Q, Wu J. Research Progress，Theoretical Foundations，and Future Prospects for Improving the Efficiency of Resource Allocation in Technological Innovation. Scientific Management Research, 2025, (1): 10-18.
[6] Fan J P， Zhao Y Y, Wu M Q. Chinese Science and Technology Innovation Resources Allocation Based on the Improved Cross-Efficiency Method. Forum on Science and Technology in China, 2017, (12): 12-40.
[7] Ding H. The New Challenges on S&T Resource Allocation and Strategies Analysis. Studies in Science of Science, 2005, (04): 474-480.
[8] Farrell M J. The Measurement of Productive Efficiency. Journal of the Royal Statistical Society． Series A(General), 1957, (120): 253-290.
[9] Ren W H. Research on Dynamic Comprehensive Evaluation of Allocation Efficiency of Green Science and Technology Resources in China’s Marine Industry. Marine Policy, 2021, 131: 2-7.
[10] Shi A N, Xu Q L. An empirical analysis of allocation efficiency of science & technology resources in China based on super-efficiency DEA and Malmquist index model. Sci. Technol. Manag. Res, 2015, 35: 54-59.
[11] Zamanian G R, Shahabinejad V, Yaghoubi M. Application of DEA and SFA on the Measurement of Agricultural Technical Efficiency in MENA Countries. International Journal of Applied Operational Research, 2013, 3(2): 43-51.
[12] Hsieh C-T, Klenow PJ. Misallocation and manufacturing TFP in China and India. Quarterly Journal of Economics. 2009, 124(4): 1403-1448.
[13] Leoncini R. The Nature of Long- run Technological Change： Innovation， Evolution and Technological Systems . Research Policy, 1998, 27(1): 75-93.
[14] Ekboir J M. Research and Technology Policies in Innovation Systems： Zero Tillage in Brazil. Research Policy, 2003, 32(4): 573-586.
[15] Tone K, Tsutsui M. An Epsilon-based Measure of Efficiency in DEA-A Third Pole of Technical Efficiency. European Journal of Operational Research, 2010, 207(3): 1554-1563.
[16] Malmquist S. Index Numbers and Indifference Curves .Trabajos de E-statistica, 1953, 4(2): 209-242.
[17] Fare Grosskopf S, Norris M, et al. Productivity Growth, Technical Progress and Efficiency Change in Industrialized Countries .American Economic Review, 1994, 84(1): 66- 83.
[18] Cui W Y, Shadow and Spillover: The Influence of Neighboring Innovative Cities on Regional Innovation Growth. China Economic Review, Elsevier, 2025, 90(C).
[19] Kerr W R, Robert-Nicoud F. Tech Clusters. Journal of Economic Perspectives, 2020, 34(3): 50-76.
[20] Zang S W, Chen H H, Mei L. Research on the Relationship between Capability Evolution, Institutional Supply and Radical Innovation. Studies in Science of Science, 2021, 39(05): 930-939.
[21] Hou J X. Theoretical Logic and Path Coupling of Regional United Front Cooperation Facilitating Coordinated Regional Development: From the Perspective of United Front Practice Based on the Coordinated Development of the Beijing-Tianjin-Hebei Region. Journal of Hebei Institute of Socialism, 2025(2): 72-80.