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Research on Transformation Efficiency of Scientific and Technological Achievements in Henan Province of China Based on Three-Stage DEA Model

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ABSTRACT

The transformation of scientific and technological achievements (TSTA) constitutes a central mechanism for advancing an innovation-led development agenda and plays a vital role in strengthening innovation capacity within Henan Province. To support the long-term improvement of the transformation efficiency of scientific and technological achievements in Henan and comparable urban areas (TESTA), this study applies a combined three-stage Data Envelopment Analysis (DEA) and Malmquist Index (MI) approach to assess both the static and dynamic characteristics of TESTA across 18 cities in the province. In addition, the Dagum Gini coefficient is utilised to measure disparities in TESTA across regions and to decompose their respective contributions. The main outcomes indicate the following: (1) TESTA levels in Henan are strongly shaped by governmental investment in science and technology, the prevailing research climate, and overall economic conditions within each locality. (2) Once external environmental influences and stochastic disturbances are filtered out, the TESTA of most cities shows a marked reduction relative to baseline results, accompanied by substantial variability across regions. (3) Analysis of the MI and its decomposed indices demonstrates that shifts in technological progress (Tech) serve as the principal endogenous force underpinning TESTA. (4) Findings from the Dagum Gini coefficient reveal that variations between regions are the major source of inequality in the provincial development of TSTA. Collectively, these insights offer practical guidance for decision-makers seeking to strengthen TESTA, highlighting the importance of enhancing scale efficiency, accelerating technological advancement, and adopting region-specific development pathways.

1. Introduction

Against the backdrop of accelerating global integration and rapid technological advancement, China has shifted from a phase of high-speed expansion towards a development pattern emphasising sustainable, high-quality growth [8; 9]. This transition marks a crucial moment in reshaping national

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development pathways, improving economic structures, and transforming underlying growth drivers. Innovation in science and technology has emerged as the dominant force stimulating economic progress across national and regional scales [4]. Within this broader context, TSTA constitutes a core mechanism enabling the implementation of innovation-led development strategies [16; 17]. Effective TSTA strengthens the interaction between science and industry, supports industrial upgrading, and contributes to high-quality economic performance.

According to the China Patent Survey Report 2023 released by the State Intellectual Property Office, the integration of technological innovation with economic activity remains essential; however, the industrialisation rate of invention patents in China remains below 40%, significantly trailing the levels observed in advanced economies in Europe and North America. Henan Province, as a major economic and demographic region, faces notable challenges in its TSTA. Despite substantial and rapidly increasing investment in innovation, the province still lags behind regions such as Jiangsu, Shandong, Zhejiang, and Guangdong in the scale of high-tech firms and technology-oriented small and medium-sized enterprises. Persistent shortcomings, including limited availability of critical technologies, suboptimal transformation outcomes, and pronounced regional disparities, continue to hinder development [21].

Pronounced differences in TESTA exist among cities within Henan Province. These disparities affect the overall scientific and technological competitiveness of the province and, to some extent, constrain coordinated regional economic development. For this reason, the present study examines TSTA and its spatial heterogeneity within Henan. Using a three-stage DEA–MI framework and panel data from 18 prefecture-level cities from 2017 to 2021, efficiency levels are assessed while simultaneously decomposing regional disparities through the Dagum Gini coefficient approach. By exploring the underlying mechanisms, the study identifies the strengths and limitations of the current transformation landscape and pinpoints the principal determinants shaping TESTA across cities, with the aim of supporting more precise local policy design.

As the key link bridging scientific and technological innovation with industrial deployment, TSTA efficiency directly influences national capacity for technological self-reliance. Prior research generally concentrates on three themes: regional variation, industrial characteristics, and specific thematic domains. The predominant analytical approaches include SFA [1; 11] and DEA [5; 15]. Studies on regional patterns have shown, for instance, that scale efficiency in R&D investment tends to be stronger in western China, while eastern regions demonstrate higher technical efficiency, and overall performance in central areas remains relatively low, suggesting substantial room for improvement [20]. Other studies have identified that intra- and inter-regional collaborative innovation exert positive influences on innovation efficiency, with intra-regional collaboration being particularly critical and subject to time-lag effects [7]. Additional research has demonstrated that stronger R&D investment intensity within firms is associated with a larger share of high-tech manufacturing [10].

In the industrial domain, factors such as technological progress, investment structures, digital financial support, and stage-specific efficiency differences all shape TESTA. Research indicates that although equipment manufacturing has contributed to improvements in economic efficiency, the overall pace of TSTA within this sector has slowed, and issues of investment redundancy persist, with regional disparities playing a major role [14]. Complementary findings show that digital finance can enhance TSTA by improving resource allocation and easing redundant investment burdens [18], while other studies highlight significant efficiency differences across stages of industrial innovation [3] and reveal threshold effects associated with public funding on the commercial value of scientific and technological outputs [12].

Within thematic perspectives, domain-specific characteristics and policy mechanisms are identified as central influences on TSTA outcomes, including studies examining ecological transformation processes [13] and the role of UIRC policies in promoting knowledge creation and TSTA in universities [6].

A review of the literature reveals several gaps. First, many studies emphasise macro-level comparisons across large regions such as eastern, central, and western China, or explore inter-provincial and industrial differences, while research focused on intra-provincial, city-level patterns remains limited, reducing applicability for localised policymaking. Second, traditional DEA frameworks often neglect environmental influences and stochastic disturbances, resulting in biased efficiency estimates. By incorporating these external factors, the present study provides a more complete and realistic evaluation of TESTA. Third, earlier research largely relies on static DEA models, which cannot capture temporal variation in efficiency levels. Dynamic approaches such as those implemented here allow for the identification of evolving trends and future performance trajectories. Fourth, many studies assess overall efficiency while overlooking the specific origins of inter-regional disparities. Such differences may be reinforced by heterogeneous local policies, further aggravating imbalance. Taking these limitations into account, this study focuses on Henan Province as a representative case within central China, examining both TESTA levels and regional differences across its cities. Given the province's diverse economic and geographical conditions, the study aims to uncover the main drivers of disparities and propose targeted strategies to enhance TESTA, reduce spatial gaps, and promote sustainable regional development.

The key marginal contributions of this study are summarised as follows: (1) Unlike research primarily centred on macro- or inter-provincial comparisons, this study conducts a fine-grained assessment of each city within Henan, providing policy recommendations that are more aligned with local realities and thus more operational for provincial and municipal authorities. (2) The analysis incorporates external environmental conditions and stochastic factors into the assessment of TESTA, significantly improving upon traditional DEA techniques and offering a more accurate reflection of uncertainties in the transformation process. (3) By integrating dynamic assessment methods, the study identifies time-dependent patterns in TESTA, enabling not only an understanding of present efficiency changes but also insights useful for long-term planning. (4) Beyond evaluating overall provincial performance, the study investigates intra-provincial disparities and their underlying causes, deepening understanding of the implications of regional policy differences for TSTA and providing a basis for strategies aimed at reducing spatial inequality.

2. Research Design

2.1 Three-Stage DEA Model

Stage 1: Traditional DEA methodologies mainly include the CCR and BCC models [2]. The CCR model evaluates decision-making units (DMUs) using a linear combination framework. In comparison, the BCC model offers greater flexibility, extending the CCR framework to accommodate variable returns to scale. This enables the distinction between inefficiencies arising from scale versus those from technical factors. In this study, an input-oriented DEA model with variable returns to scale is adopted [19]. The BCC model is formulated as follows:

Consider a system m DMUs, with each DMU described by v input indicators and u output indicators. Each DMU forms a production point $H(v,u)$. The total input of type a for j DMUs is $x_{a,j}$, then the total output of type b is $y_{b,j}$, where,$a = 1,2,\cdots,v$; $b = 1,2,\cdots,u$; $j = 1,2,\cdots,m$.

$$min\left[\theta_j - \varepsilon\left(\sum_{b=1}^{u} S_b^+ + \sum_{a=1}^{v} S_a^-\right)\right] \qquad (1)$$

$$\min\left[\theta_j - \varepsilon\left(\sum_{b=1}^{u} S_b^+ + \sum_{a=1}^{v} S_a^-\right)\right]$$

$$s.t.\begin{cases} \sum_{j=1}^{m} x_{a,j}\eta_j + S_a^- \\ \sum_{j=1}^{m} y_{b,j}\eta_j - S_b^+ \\ \sum_{j=1}^{m} \eta_j = 1, \eta_j \geq 0 \\ S_a^- \geq 0, S_b^+ \geq 0 \end{cases} \quad (2)$$

Among them, ε represents a non-Archimedean infinitesimal quantity. S_a^- and S_b^+ are represented as slack variables for input and output. The decision variable is denoted by η. θ indicates the efficiency.

Stage 2: The initial efficiency evaluation does not consider the influence of environmental conditions, stochastic disturbances, or managerial inefficiencies. To address this, the SFA model is applied at this stage. Environmental variables are introduced as explanatory variables, enabling the separation of the effects of environmental factors, random noise, and managerial inefficiency. The model construction process is detailed as follows:

$$P_{lc} = g(U_c\,; \beta_l \quad) + a_{lc} + b_{lc}\,; c = 1,2 \cdots, C\,; l = 1,2, \cdots, L \quad (3)$$

The relaxation value is P_{lc}. The environment variable is U_c. β_n represents the environment variable coefficient. the mixture error term is $a_{lc} + b_{lc}$. a_{lc} is the random disturbance, and b_{lc} is managerial inefficiency. Where $a \sim L(0, \partial_a^2)$ is the random error term, representing the influence of random disturbance factors on the input slack variables. b is management inefficiency.

The cost-function representation of the managerial inefficiency model is expressed as follows:

$$Y[u_{lc}|a_{lc} + b_{lc}] = \frac{\partial\eta}{1+\eta^2}\left[\frac{\varphi\left(\frac{\varepsilon\eta}{\partial}\right)}{\phi\left(\frac{\varepsilon\eta}{\partial}\right)} + \frac{\varepsilon\eta}{\partial}\right] \quad (4)$$

$$\begin{cases} \eta = \frac{\sigma_u}{\sigma_v} \\ \varepsilon = a + b \\ \partial^2 = \partial_a^2 + \partial_b^2 \end{cases} \quad (5)$$

Where, φ represents the functions. ϕ is the distribution functions. The model representing random disturbances is formulated as follows:

$$Y[a_{lc}|a_{lc} + b_{lc}] = P_{lc} - U_c\beta_l - Y[b_{lc}|a_{lc} + b_{lc}] \quad (6)$$

The formula for adjusting the input variables is as follows:

$$Q_{lc}^A = Q_{lc} + \left[max\left(g\left(U_c\,; \hat{\beta_l}\right)\right) - f\left(U_c\,; \hat{\beta_l}\right)\right] + [max(a_{lc}) - a_{lc}] \quad (7)$$

Q_{ni}^A and Q_{ni} respectively represent the adjusted and unadjusted inputs. External environmental factors are processed using formula $\left[max\left(f\left(U_c\,; \hat{\beta_l}\right)\right) - g\left(U_c\,; \hat{\beta_l}\right)\right]$. All DMUs under the same level of luck use formula $[max(a_{lc}) - a_{lc}]$.

Stage 3: Following the second-stage adjustment of input variables, which isolates environmental factors and managerial inefficiencies, the BCC model is reapplied to evaluate the TESTA. The resulting efficiency is expressed as comprehensive technical efficiency (TE), which is decomposed into pure technical efficiency (PTE) and scale efficiency (SE), such that TE = PTE × SE.

2.2 MI Model

The DEA model is limited to assessing the static TESTA of Henan cities and cannot capture the temporal evolution of efficiency. To examine the dynamic trends in TESTA over time, this study employs the MI model, specified as follows:

$$MI_r(A^V, B^V, A^{V+1}, B^{V+1}) = \left[\frac{D_r^V(A_r^{V+1}, B_r^{V+1})}{D_r^V(A_r^V, B_r^V)} \times \frac{D_r^{V+1}(A_r^{V+1}, B_r^{V+1})}{D_r^{t+1}(A_r^V, B_r^V)}\right]^{1/2} \quad (8)$$

$$MI_r = \frac{D_r^{V+1}(A^{V+1}, B^{V+1})}{D_r^V(A^V, B^V)} \times \left[\frac{D_r^V(A^{V+1}, B^{V+1})}{D_r^{V+1}(A^{V+1}, B^{V+1})} \times \frac{D_r^V(A^V, B^V)}{D_r^{V+1}(A^V, B^V)}\right]^{1/2} = Effch \times Tech$$

$$= Effch \times Pech \times Sech \quad (9)$$

A and B represent input and output variables, respectively. D represents the distance function. If MI_r is greater than 1, then total factor productivity (Tfp) tends to increase, otherwise, it tends to decrease. Tfp is decomposed into two components: technical efficiency change (Effch) and technological progress (Tech). Furthermore, Effch itself is subdivided into pure technical efficiency change (Pech) and scale efficiency change (Sech).

2.3 Dagum Gini Coefficient Model

The Gini coefficient is an important indicator of inequality in the distribution of income or wealth. Dagum further decomposed the Gini coefficient and divided it into three parts: intra-regional difference contribution(G_w), inter-regional difference contribution,(G_{nb}) and super-variable density contribution (G_t). This decomposition facilitates the identification of sources underlying inter-regional disparities and effectively elucidates the cross-cutting impacts among subgroups. The precise formulation is detailed in reference.

Where, overall Gini coefficient(G):

$$G = G_w + G_{nb} + G_t \quad (8)$$

2.4 Study Area

In accordance with the Central Plains Urban Agglomeration Development Plan, the 18 prefecture-level cities in Henan Province are categorized into three principal regions (see Fig.1):

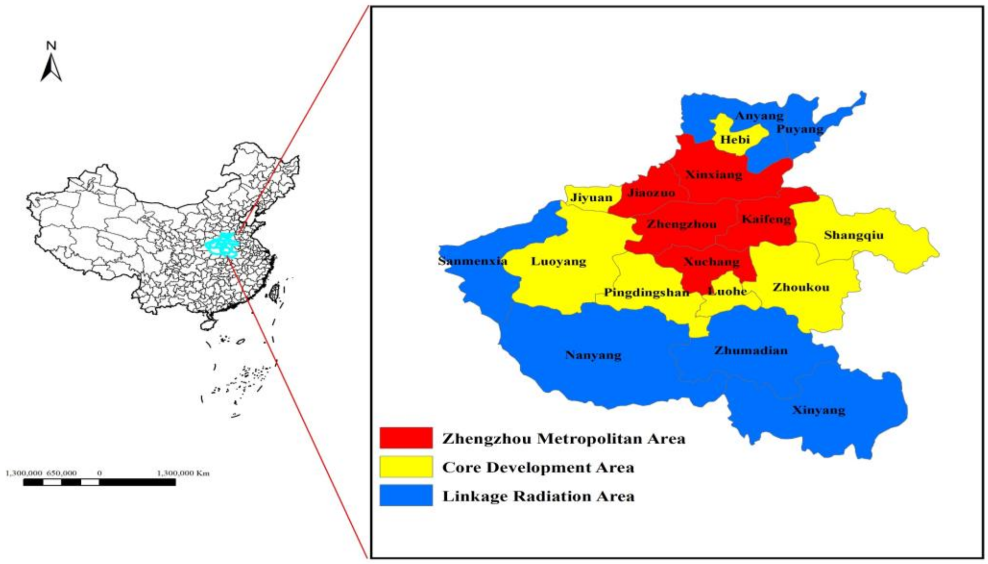

Fig.1: Study Area

The Zhengzhou Metropolitan Area (ZMA), the Core Development Area (CDA), and the Linkage Radiation Area (LRA). The ZMA comprises Zhengzhou, Kaifeng, Xinxiang, Jiaozuo, and Xuchang. The

CDA includes Luoyang, Pingdingshan, Hebi, Luohe, Shangqiu, Zhoukou, and Jiyuan. The LRA consists of Anyang, Puyang, Sanmenxia, Nanyang, Xinyang, and Zhumadian.

2.5 Indicator System Construction

Considering the practical conditions of TSTA across the cities of Henan Province, this study selects indicators primarily informed by existing work concerning talent resources and financial inputs. Three input variables are employed: full-time equivalent R&D personnel, internal R&D expenditure, and government spending on science and technology. Drawing on prior research, output indicators are identified from the perspectives of scientific and technological production, technological effectiveness, and market-oriented returns. Four output variables are used: the number of accepted patent applications, the number of granted patents, the value of contracts in the technology market, and the sales revenue of newly developed products. Reviewing the current literature on TESTA reveals that environmental conditions are rarely incorporated into analytical frameworks, leading to potential measurement bias. To address this limitation, the present study incorporates environmental variables selected from three dimensions: government financial support, scientific research climate, and the level of regional economic development.

2.5.1 Government Financial Support

Government financial support is one of the most direct indicators of a region's commitment to innovation. Stronger fiscal backing enhances the capacity of local innovation systems by offering grants, subsidies, and stable financial assurance. Such support reduces the cost and risk of R&D activities for firms, research institutes, and universities, while also signalling policy emphasis. In this study, government support is measured using the ratio of local financial expenditure on science and technology to total local government expenditure.

2.5.2 Scientific Research Atmosphere

The scientific research atmosphere reflects the extent to which cities benefit from the concentration of research institutions, universities, and enterprise laboratories. Higher levels of institutional clustering encourage knowledge spillovers, collaboration, and interdisciplinary exchange, thereby forming a supportive innovation ecosystem. A favorable scientific research climate lowers the transaction costs associated with innovation, stimulates creative inquiry, and advances the diffusion of research results into practical application. To represent this factor, the proportion of research institutions within each city relative to the total number of such institutions in the province is used.

2.5.3 Regional Economic Development Level

Regional economic development is also closely linked to TSTA. Cities with higher per capita GDP tend to have more extensive markets for emerging products, stronger infrastructure, easier access to capital, and greater attractiveness for skilled professionals. These conditions improve the capacity to absorb and apply technological advances. In this study, per capita GDP is selected as the indicator of regional economic development. The complete set of variables is shown in Table 1.

Table 1
TSTA Evaluation System

Type	Indicators of Relevance	Unit
Input Indicators	Full-Time Equivalent of R&D Personnel	Person-Year
	Internal Expenditure of R&D Funds	10000 Yuan
	Financial Expenditure on Science and Technology	Billion Yuan
Type	**Indicators of Relevance**	**Unit**
Output Indicators	Amount of Patent Applications Accepted	Piece

	Amount of Patent Authorization	Piece
	Amount of Technology Market Contracts	10000 Yuan
	Sales Volume of New Products	10000 Yuan
Environmental Variable Indicators	Government Financial Support	%
	Scientific Research Atmosphere	%
	Regional Economic Development Level	10000 Yuan /Person

2.6 Data Sources

Considering the defined research boundaries and the availability of relevant statistical indicators, the dataset used in this study includes information from 18 prefecture-level cities in Henan Province for the years 2017–2021. The selection of TSTA input and output variables, along with environmental indicators, is based on the accessibility and completeness of the required data. The primary sources of the sample dataset are the Henan Provincial Statistical Yearbooks (2017–2021), the China Science and Technology Statistical Yearbooks (2017–2021), and publicly released data from municipal statistical authorities.

3. Results

3.1 Static Analysis of the Efficiency

3.1.1 The Results of the First Stage DEA

In the first stage, the assessment relies solely on the unadjusted input and output indicators. The BCC framework is applied to measure TESTA under these conditions. Owing to space constraints, only the mean efficiency values are reported (see Table 2).

Table 2
The Average Value of the TESTA

Region	First Stage			Third Stage		
	TE	PTE	SE	TE	PTE	SE
Zhengzhou	1	1	1	1	1	1
Kaifeng	0.663	0.705	0.944	0.597	0.704	0.841
Xinxiang	0.980	1	0.980	0.998	1	0.998
Jiaozuo	1	1	1	1	1	1
Xuchang	0.913	0.954	0.955	0.909	0.954	0.952
ZMA	0.911	0.932	0.976	0.901	0.932	0.958
Luoyang	0.868	0.897	0.962	0.867	0.896	0.967
Pingdingshan	0.503	0.517	0.974	0.481	0.519	0.927
Hebi	0.802	1	0.802	0.510	1	0.510
Luohe	0.819	0.960	0.857	0.677	0.988	0.685
Shangqiu	0.694	0.761	0.922	0.618	0.760	0.822
Zhoukou	0.550	0.700	0.814	0.451	0.685	0.681
Jiyuan	1	1	1	0.917	1	0.917
CDA	0.748	0.834	0.904	0.646	0.835	0.787
Anyang	0.737	0.761	0.962	0.700	0.762	0.902
Puyang	0.672	0.804	0.835	0.561	0.563	0.996
Sanmenxia	0.420	0.549	0.792	0.360	0.554	0.673
Nanyang	0.710	0.733	0.968	0.683	0.731	0.934
Xinyang	0.899	0.952	0.936	0.801	0.953	0.835
Zhumadian	0.739	0.839	0.884	0.630	0.823	0.771
LRA	0.696	0.773	0.896	0.623	0.731	0.852
Grand Average	0.776	0.841	0.922	0.709	0.827	0.856

As indicated in Table 2 and Fig. 2, when environmental conditions and stochastic influences are excluded, substantial disparities emerge in TESTA across the cities. This pattern reflects notable variation in each city's capacity to undertake TSTA. Overall, the mean TE for Henan's cities during 2017–2021 is 0.776, while the corresponding PTE and SE values are 0.841 and 0.922, respectively. Only SE approaches an efficient state, suggesting generally weak performance in TESTA across the 18 cities. At the individual city level, Zhengzhou, Jiaozuo, and Jiyuan record TE and SE values of 1, representing approximately 17% of the province and indicating fully efficient input–output configurations in these locations. With respect to PTE, five cities—Zhengzhou, Hebi, Xinxiang, Jiaozuo, and Jiyuan—achieve a value of 1 and lie on the efficiency frontier, accounting for 28% of the sample. The findings suggest that inadequate PTE is the predominant constraint contributing to the overall low TESTA performance.

According to the regional breakdown, the mean TE values for the ZMA, CDA, and LRA were calculated as 0.911, 0.748, and 0.696, respectively, indicating a pattern of ZMA > CDA > LRA. Among the three areas, only the ZMA exceeded the provincial TE average. Examination of PTE and SE revealed that the ZMA also outperformed the CDA and LRA on both metrics and similarly recorded values above the provincial mean. This pattern is likely linked to the comparatively advanced economic conditions of the ZMA, together with its stronger institutional support, more active technological progress, and greater capacity to attract skilled personnel.

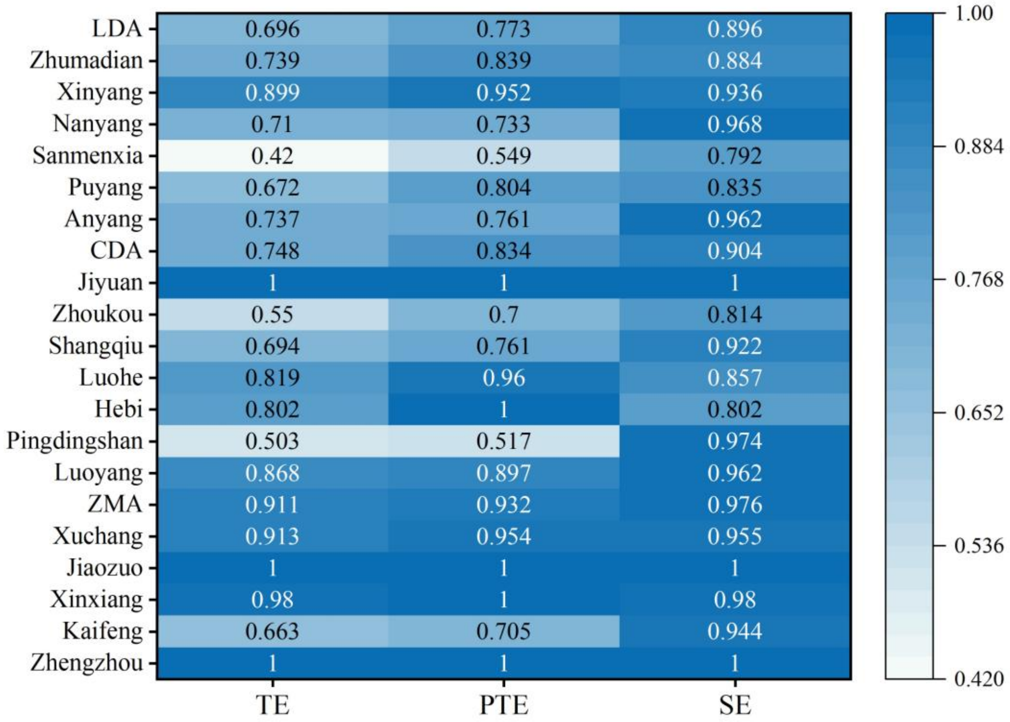

Fig.2: The Results of the First Stage DEA

3.1.2 SFA Model Analysis

In the first stage, TESTA was influenced by environmental conditions, stochastic disturbances, and managerial inefficiencies, which introduced potential biases into the results. To correct for these effects, the second stage utilises the SFA framework (see Table 3). The input slack variables derived from the first stage serve as the dependent variables, while environmental indicators—including government financial support, scientific research atmosphere, and regional economic development—are incorporated as explanatory factors.

Table 3
SFA Model Regression Results

Variable	Full-Time Equivalent of R&D Personnel	Internal Expenditure of R&D Funds	Financial Expenditure on Science and Technology
Constant Term	13.533	-69378.334***	1.597***
Government Financial Support	-10412.398***	2511970.700***	3.485
Scientific Research Atmosphere	996.471***	-114246.850***	2.532
Regional Economic Development Level	0.001	0.268**	0.00026***
σ^2	166241.900***	5171246900.000***	98.906***
γ	0.522***	0.621***	0.986***
Log Likelihood Function	-646.409	-1107.480	-159.817
LR Test Value	29.579***	22.238***	46.430***

Note: *, **, and *** respectively indicate significance at 10%, 5%, and 1% significance levels.

The analysis indicates that the LR test for the input slack variables in TSTA is significant at the 1% level, confirming that TESTA is substantially influenced by the three environmental factors. This outcome validates the appropriateness of employing the SFA regression model. Both and are statistically significant at the 1% level, with values ranging between 0 and 1, underscoring the necessity of controlling for environmental conditions and stochastic disturbances. In the SFA regression, a positive coefficient for an environmental variable implies a direct relationship with the input slack variables. In practical terms, an increase in the environmental variable results in higher inputs or reduced outputs, thereby lowering TESTA. Conversely, a negative coefficient indicates an inverse relationship, where an increase in the environmental variable reduces inputs or enhances outputs, leading to improved TESTA. The detailed findings of these analyses are presented as follows:

3.1.3 Government Financial Support

In practice, the proportion of local financial expenditure on science and technology relative to total local spending significantly affects only R&D personnel and R&D expenditure. Specifically, it exhibits a negative relationship with R&D personnel and a positive relationship with R&D expenditure. Local government budgets typically allocate resources across science and technology innovation, education, employment, healthcare, social security, and environmental protection. To enhance the efficiency of TSTA, cities in Henan Province should prioritize investment in the development of scientific and technological talent, including recruitment, training, and practical deployment of highly skilled personnel. This approach optimizes the utilization of research talent and the allocation of resources. Conversely, excessive financial input into research funding may result in redundancies and inefficient resource use.

3.1.4 Scientific Research Atmosphere

The scientific research atmosphere exerts a statistically significant impact solely on R&D personnel and R&D expenditure, both at the 1% level, while showing no measurable effect on financial spending for science and technology. Specifically, it demonstrates a positive association with R&D personnel and a negative association with R&D expenditure. These findings indicate that enhancing the research climate requires not only fostering researchers' confidence and self-efficacy but also ensuring the effective allocation and utilization of financial resources. Optimizing the distribution of science and technology funding and maximizing its operational efficiency is therefore essential for achieving the most effective deployment of research resources.

3.1.5 Regional Economic Development Level

Per capita GDP exhibits a positive influence on all three input variables, with the relationships between R&D expenditure and financial expenditure on science and technology attaining significance at the 1% level. As an indicator, per capita GDP partially reflects regional economic development, where higher values typically correspond to more advanced local economies. Nevertheless, increases in per capita GDP may also contribute to redundancies in R&D and financial inputs, leading to expanded slack variables and reduced efficiency in the allocation of research resources. This phenomenon largely arises from the uneven economic development within Henan Province, pronounced disparities in wealth, and escalating regional polarization, which limit the capacity of per capita GDP to fully represent the actual level of regional development.

3.1.6 The Adjusted DEA Results

Following the second-stage SFA regression, the effects of environmental conditions and stochastic disturbances were removed. The adjusted input variables were recalculated using the BCC model in conjunction with the original output indicators from the first stage (see Table 1 and Fig. 3).

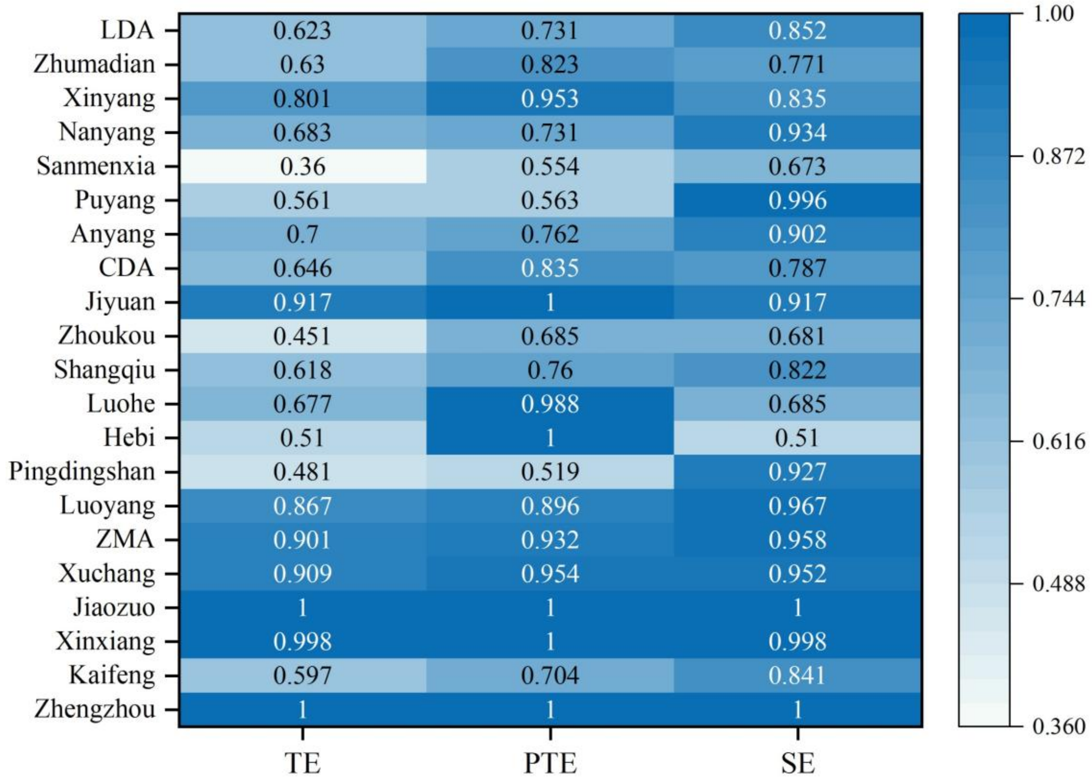

Fig.3: The Results of Adjusted DEA

These recalculated efficiency values are more scientifically robust, rational, and reflective of actual performance than those obtained initially. The average TE across Henan Province declined from 0.776 to 0.709, representing an 8.63% reduction relative to the first stage. Average PTE decreased from 0.841 to 0.827, a fall of 1.66%, while the adjusted mean SE dropped from 0.922 to 0.856, a reduction of 7.16%. Zhengzhou and Jiaozuo remained at the frontier for TE, PTE, and SE. After accounting for external environmental influences, the decline in TESTA is no longer predominantly driven by PTE, as observed in the first stage, but is primarily attributable to the adjusted SE. These results indicate that enhancing TESTA in Henan's cities cannot be achieved merely by increasing technological investment; efficiency improvements in scale and resource utilization are essential.

3.1.7 The Average Value of Efficiency Before and After Adjustment from 2017 to 2021

As shown in Fig. 4, prior to adjustment, the average TE of TSTA exhibited a general upward trend, with the exception of 2020, when a decline occurred, likely due to the COVID-19 outbreak. Following adjustment, both TE and SE in Henan Province generally decreased on an annual basis, although PTE showed modest increases in certain years. These patterns indicate that, without accounting for external environmental influences, TESTA was substantially overestimated, particularly in terms of SE. Apart from 2017, average PTE consistently exceeded SE, reinforcing the conclusion that insufficient SE remains the principal constraint on improving TESTA performance in the province.

Adjusted PTE experienced a marked increase in 2017, reaching its peak in 2020, before declining thereafter. This trend can be partly attributed to the 2017 Implementation Programme for the Construction of a Technology Transfer System in Henan Province, which emphasised the establishment of a technology transfer framework aligned with principles of scientific and technological innovation, technology transformation, and industrial development. The programme aimed to strengthen both the supply and transformation capacities of scientific and technological outputs, thereby enhancing TSTA, which explains the observed rise in PTE in 2017 and its peak in 2020. The subsequent decline is likely linked to COVID-19, which restricted mobility and disrupted transformation activities.

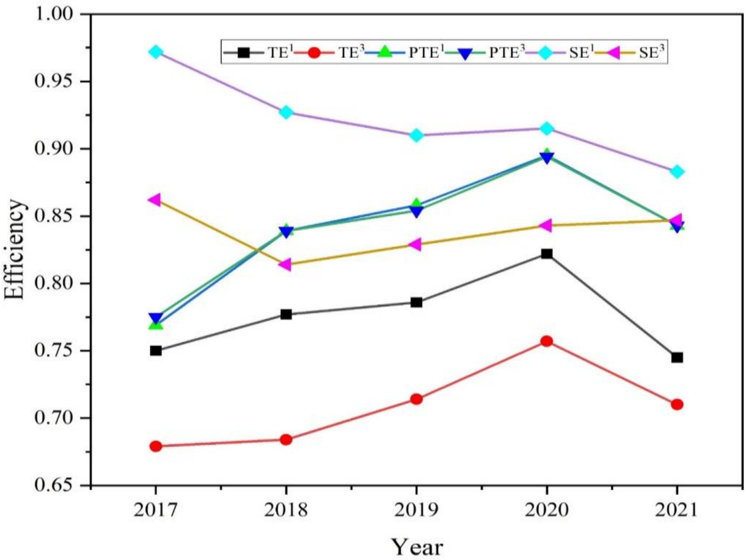

Fig.4: Trends in the Average Efficiency Before and After Adjustment. “1” Indicates the First Stage (Before Adjustment), and “3” Indicates the Third Stage (After Adjustment).

Adjusted SE initially fell sharply in 2017 but then recovered gradually. That year, Henan faced transitional pressures from economic restructuring, industrial upgrading, and the shift from traditional to emerging growth drivers, which slowed economic expansion. The 2017 National Economic and Social Development Plan for Henan outlined objectives such as stabilising growth, optimising industrial structures, and deepening reforms, which may have reduced SE as slower growth typically lowers resource allocation efficiency. Additionally, the 2017 Henan Provincial Government Work Report promoted policies aimed at stabilising industrial growth, stimulating non-public economic activity, mitigating risks, and advancing supply-side structural reform. These interventions contributed to the gradual recovery of average SE in 2018.

3.1.8 Average Efficiency of Each City Before and After Adjustment

To investigate the spatial variations in TESTA and the decomposition of efficiency across the first and third stages in Henan Province, efficiency scores before and after adjustment were visualised using a radar chart (see Fig. 5). From the perspective of TE, most cities experienced declines in the third stage, with Xinxiang being a notable exception. The CDA, including Hebi, Luohe, and Zhoukou, exhibited pronounced reductions. Only Zhengzhou and Jiaozuo maintained relatively high efficiency, indicating that their superior performance largely reflects advantageous environmental conditions. Conversely, Jiyuan shifted from technically effective (TE = 1) in the first stage to non-technically effective (TE < 1) in the third stage, suggesting that its initial technical efficiency was inflated due to favourable external conditions.

For PTE, the number of cities attaining efficiency increased in the first stage relative to TE, but remained unchanged in the third stage. Notably, five cities—Pingdingshan, Luohe, Anyang, Sanmenxia, and Xinyang—demonstrated improvements in PTE during the third stage, whereas all other cities experienced declines. Except for Luohe and Xinyang, PTE in the remaining cities fell below the provincial average of 0.827, indicating that technical management and innovation capacity remain relatively weak in these areas. Regarding SE, Zhengzhou, Jiaozuo, and Jiyuan were technically effective in the first stage. However, in the third stage, Jiyuan's SE declined below the efficiency threshold, revealing that external environmental factors constrained the city's ability to fully exploit its scale potential. Several cities, although not technically efficient, maintained SE values above the provincial average of 0.856, including Xinxiang (0.998), Xuchang (0.952), Luoyang (0.967), Pingdingshan (0.927), Jiyuan (0.917), Anyang (0.902), Puyang (0.996), and Nanyang (0.934), collectively representing approximately 44% of the sample. For sustained economic advancement, these cities should prioritise scale optimisation, industrial integration, technological innovation, and market expansion to enhance SE and strengthen the effectiveness of TSTA implementation.

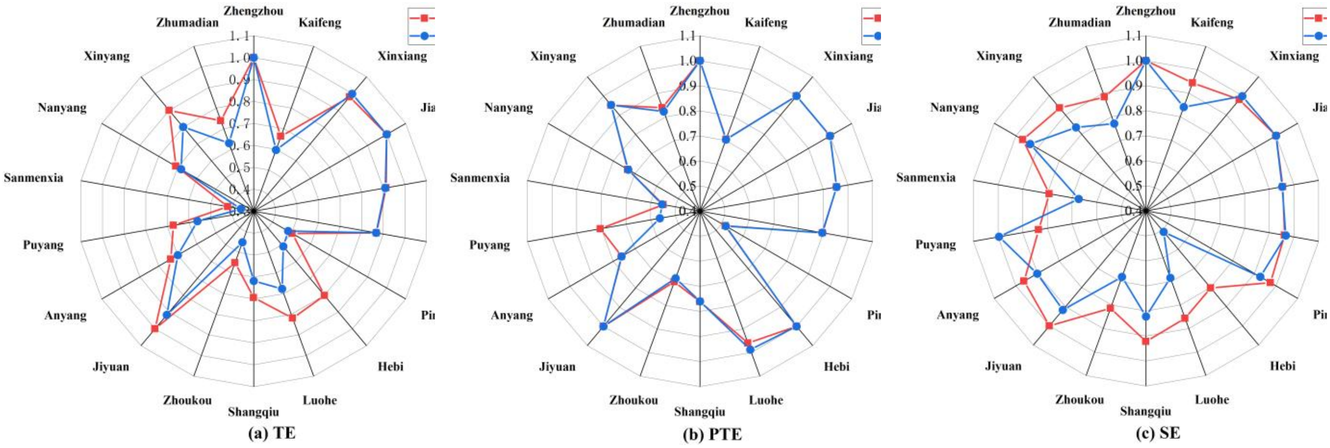

Fig.5: The Average Efficiency of Each City Changes Before and After Adjustment

3.1.9 Three Regional Distribution Characteristics

After controlling for external environmental factors and stochastic disturbances, substantial changes in TESTA were observed across the three regions. Both TE and SE exhibited declines (see Table 4), whereas PTE remained stable in the ZMA and showed a slight increase in the CDA. In the third stage, TE continued to follow the pattern ZMA > CDA > LRA, highlighting the ZMA's superior capability in resource allocation and technical proficiency for TSTA. The LRA recorded the lowest PTE, indicating an urgent need to enhance the efficiency of resource utilization. Meanwhile, the CDA demonstrated the lowest SE, suggesting that this region should focus on optimizing industrial operation mechanisms, promoting the development of industrial clusters, and establishing a more balanced supply structure within the TSTA system.

Table 4
Three Regional Efficiency Results

Area	First Stage			Third Stage		
	TE	PTE	SE	TE	PTE	SE
ZMA	0.911	0.932	0.976	0.901	0.932	0.958
CDA	0.748	0.834	0.904	0.646	0.835	0.787
LRA	0.696	0.773	0.896	0.623	0.731	0.852

3.1.10 The Spatial Pattern of Efficiency Changes after Adjustment

To visualise the spatial and temporal evolution of TESTA across Henan’s cities, the natural breakpoint method within GIS software was employed to classify efficiency into three tiers. Given that DEA-derived efficiency values are relative, the analysis focused on the years 2017, 2019, and 2021, with the corresponding city-level TESTA values illustrated in Fig. 6. Fig. 6 highlights pronounced geographic disparities in TESTA among the cities. Zhengzhou, Jiaozuo, Xinxiang, and Xuchang consistently occupied the top tier from 2017 to 2021. The ZMA maintained high and stable TESTA levels, with influence gradually extending to surrounding regions. In contrast, Luoyang and Jiyuan within the CDA declined from the top tier in 2017 to the second tier by 2021. Anyang in the LRA exhibited steady progress, rising from the third tier in 2017 to the second tier in 2019, and achieving the top tier by 2021. The remaining cities experienced fluctuations within the three tiers throughout the period.

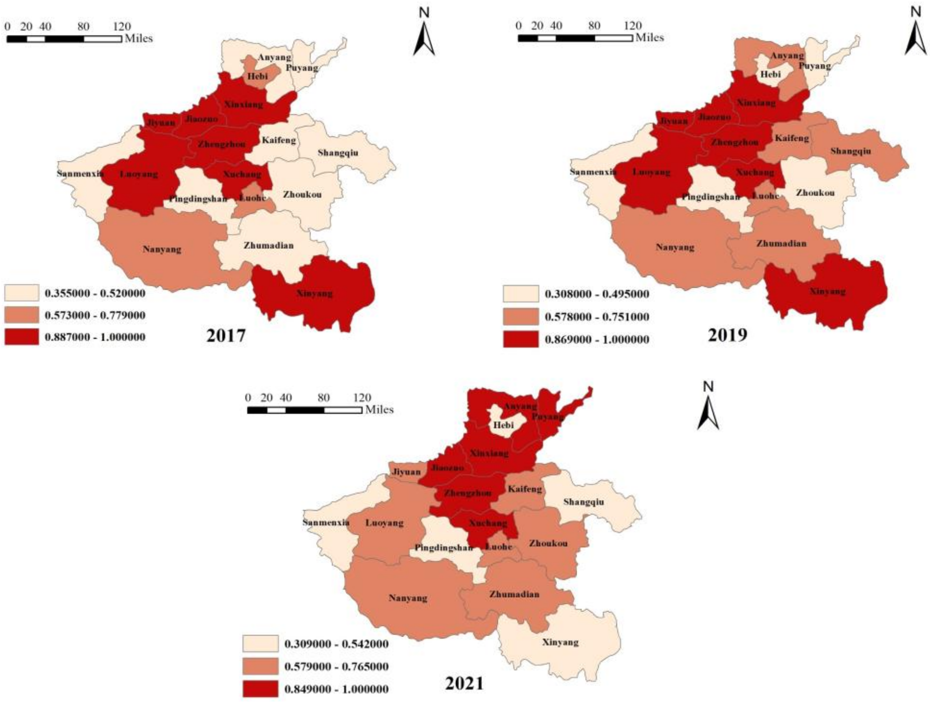

Fig.6: The Spatial-Temporal Pattern of Efficiency of Each City after Adjustment

3.2 Dynamic Analysis of the Efficiency

The MI framework was employed to examine the dynamic evolution of TESTA across Henan’s cities and to analyse intercity differences (see Table 5 and Fig. 5). As presented in Table 5, between 2017 and 2021, the average Tfp was 1.104, indicating that TESTA expanded at an average annual rate of 10.4%.

Table 5
Adjusted MI Decomposition Results

Year	Effch	Tech	Pech	Sech	Tfp
2017-2018	1.020	1.078	1.034	0.986	1.099
2018-2019	1.053	0.920	1.005	1.048	0.968
2019-2020	1.071	1.128	1.031	1.039	1.208
2020-2021	0.937	1.232	0.953	0.983	1.154
Average	1.019	1.083	1.005	1.013	1.104

The decomposition of Tfp reveals that Effch exhibited a relatively stable trend over the five-year period, averaging 1.019 and reflecting a mean annual growth rate of 1.9%. In contrast, Tech experienced greater volatility, with an average value of 1.083 and a mean annual growth rate of 8.3%. Fig. 7 illustrates that the fluctuations in Tfp and Tech were closely aligned, indicating that the increase in Tfp during 2017–2021 was primarily driven by Tech. Although Effch showed a gradual upward trend, declines in Tech contributed to reductions in Tfp. This can be partly attributed to a slowdown in global economic growth, particularly following the escalation of the China–US trade dispute, which disrupted international trade and investment flows. External pressures, including weakening export demand and decelerating manufacturing growth, likely impacted high-tech and export-oriented sectors in Henan, thereby influencing both Tech and Tfp. Additionally, in 2018, Henan may have experienced structural adjustments in industrial development, requiring a transitional period to convert traditional industries into high-tech sectors.

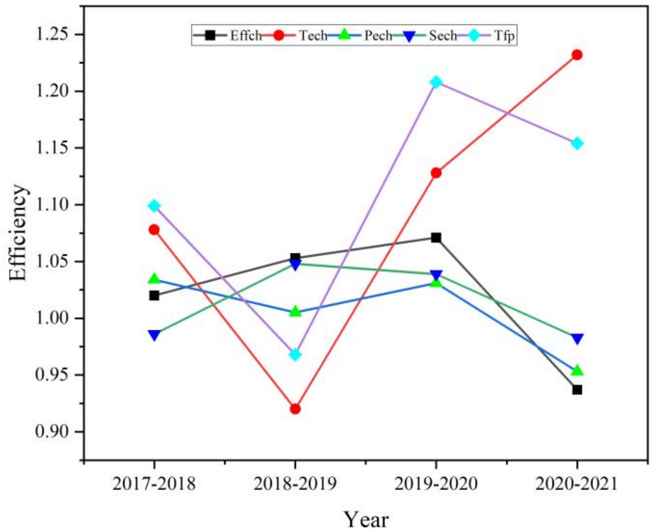

Fig.7: MI and Decomposition Index Change Trend

Based on the Effch decomposition, the average Pech from 2017 to 2021 was 1.005, corresponding to an annual growth rate of 0.5%, while the mean Sech reached 1.013, with a yearly growth rate of 1.3%. Cross-referencing these results with Fig. 5 indicates that the increase in Effch in Henan Province during 2017–2019 was predominantly driven by Sech. In contrast, from 2019 to 2021, improvements in Effch were primarily attributable to gains in Pech. This pattern reflects stage-specific variations in TESTA within the province: initial gains were largely achieved through scale efficiencies, whereas subsequent progress was primarily facilitated by technological advancement and optimisation.

3.2.1 Adjusted MI Decomposition Results by City

As illustrated in Table 6, apart from Hebi, Xinyang, and Jiyuan, Tfp exceeded 1 in the remaining cities, representing 83.3% of the sample. These findings indicate that significant progress was made in promoting TESTA across Henan Province from 2017 to 2021. Notably, Puyang achieved an average annual Tfp growth of 63.7%, largely driven by substantial gains in Tech. Conversely, Jiyuan recorded the lowest Tfp at 0.794, reflecting an average annual decline of 20.6%, primarily attributable to low Sech. This may result from a lack of large, competitive, and innovative enterprises, limited industrial agglomeration, and underutilised economies of scale, which collectively increase fixed costs and reduce resource allocation efficiency, thereby suppressing Sech and Tfp. In contrast, Kaifeng, Anyang, and Zhumadian experienced Tfp growth exceeding 20%, whereas the remaining eleven cities saw increases below 10%. Overall, the period from 2017 to 2021 demonstrates that Henan Province has achieved positive outcomes in advancing TESTA, with most cities showing improved Tfp. The exceptional growth in Puyang exemplifies the effectiveness of TSTA and innovation-oriented policies, while the decline in Jiyuan highlights structural limitations in certain cities, underscoring the need to strengthen innovation capacity and promote industrial restructuring.

Table 6
Adjusted 2017-2021 MI Decomposition Results by Each City

City	Effch	Tech	Pech	Sech	Tfp
Zhengzhou	1.000	1.083	1.000	1.000	1.083
Kaifeng	1.212	1.054	1.060	1.144	1.278
Xinxiang	1.002	1.075	1.000	1.002	1.077
Jiaozuo	1.000	1.086	1.000	1.000	1.086
Xuchang	0.989	1.049	0.975	1.015	1.038
Luoyang	0.899	1.287	0.903	0.996	1.157
Pingdingshan	1.003	1.065	0.958	1.047	1.069
Hebi	0.941	1.014	1.000	0.941	0.955
Luohe	0.961	1.071	1.000	0.961	1.030
Shangqiu	1.036	1.070	1.014	1.022	1.108
Zhoukou	1.092	1.053	1.058	1.032	1.149
Jiyuan	0.874	0.908	1.000	0.874	0.794
Anyang	1.296	1.071	1.106	1.171	1.388
Puyang	1.205	1.359	1.029	1.171	1.637
Sanmenxia	0.930	1.090	1.056	0.880	1.013
Nanyang	1.045	1.059	0.999	1.046	1.107
Xinyang	0.858	1.064	0.974	0.881	0.912
Zhumadian	1.107	1.107	0.977	1.134	1.225
Average	1.019	1.083	1.005	1.013	1.104

3.2.2 Adjusted Regional MI Decomposition Results

From a regional perspective (see Fig. 8), Tfp values for the ZMA, CDA, and LRA were 1.112, 1.037, and 1.214, respectively, indicating the order LRA > ZMA > CDA. The LRA achieved the highest Tfp, with an average annual growth rate of 21.4%, primarily driven by Tech, which significantly enhanced TESTA in the region. This demonstrates that the LRA has made notable strides in scientific and technological innovation as well as industrial structure optimisation, with Tech playing a crucial role in elevating TESTA. In contrast, the CDA recorded the lowest Tfp, falling below the provincial average. This outcome is attributable to low Effch, which in turn is linked to weak Pech, suggesting that the region lags in technology adoption and innovation, and is unable to fully exploit the potential of existing technologies. Overall, pronounced regional disparities in Tfp persist across Henan Province. Moving forward, the CDA could leverage the radiative influence of the LRA and ZMA, strengthening interregional collaboration to foster technological advancement and coordinated industrial development throughout the province.

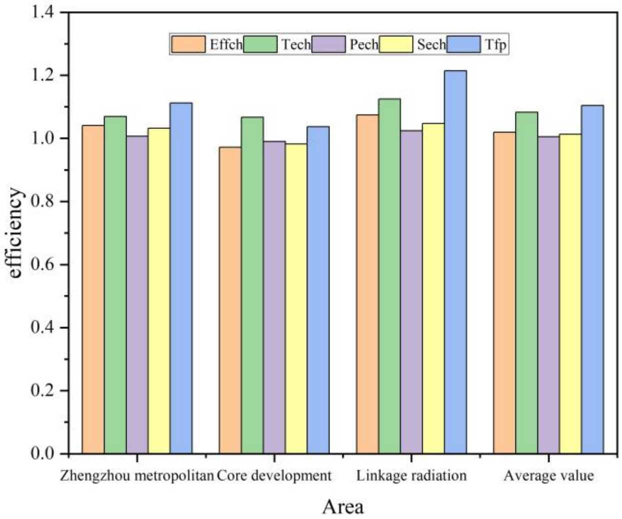

Fig.8: Adjusted Regional MI Decomposition

3.3 Analysis of Three Regional Differences in Henan Province

The above findings indicate that TESTA in Henan Province has generally improved over the study period; however, substantial regional disparities remain evident. The ZMA consistently recorded the highest average TESTA at 0.901, whereas the LRA averaged only 0.623, representing a 45% gap and highlighting pronounced interregional imbalance. Significant variations also exist within individual regions. For instance, within the LRA, Xinyang attained the highest TESTA of 0.801, while Sanmenxia registered merely 0.360, a discrepancy of 123%, reflecting considerable intra-regional inequality. To quantify the extent of imbalance in TSTA development more precisely, the Dagum Gini model was applied to compute both intra- and inter-regional Gini coefficients (see Table 7).

Table 7

Gini Coefficients and Decomposition Results in Three Regions of Henan Province

Year	G	Contribution（%）			Intra-Regional Gini Coefficient			Inter-Regional Gini Coefficient		
		G_w	G_{nb}	G_t	ZMA	CDA	LRA	ZMA - CDA	ZMA - LRA	CDA - LRA
2017	0.216	28.946	41.316	29.738	0.145	0.192	0.192	0.213	0.282	0.220
2018	0.197	27.521	49.979	22.500	0.091	0.208	0.134	0.207	0.252	0.200
2019	0.185	29.575	41.791	28.634	0.088	0.172	0.191	0.184	0.224	0.192
2020	0.163	29.001	42.700	28.299	0.057	0.160	0.160	0.187	0.160	0.176
2021	0.170	21.666	63.204	15.130	0.047	0.068	0.193	0.247	0.172	0.183
Average	0.186	27.342	47.798	24.860	0.086	0.160	0.174	0.208	0.218	0.194

The results indicate that the Gini coefficient of TESTA in Henan Province experienced fluctuations but exhibited an overall declining trend, falling from 0.216 to 0.170, a reduction of 21%. This trend reflects a narrowing of disparities in the overall level of TESTA development. Considering intra-regional differences (see Fig. 9), the average Gini coefficients for the ZMA, CDA, and LRA were 0.086, 0.160, and 0.174, respectively, suggesting the spatial pattern LRA > CDA > ZMA. This implies that cities within the LRA currently exhibit the largest developmental gaps in TSTA. Regarding temporal trends, the Gini coefficient for the ZMA remained relatively stable, decreasing markedly from 0.145 in 2017 to 0.086 in 2021, and consistently staying below the values observed in the other regions. In contrast, the CDA and LRA displayed more volatile patterns. The CDA initially increased before declining, whereas the LRA exhibited an M-shaped trajectory, characterized by alternating decreases and increases over the period.

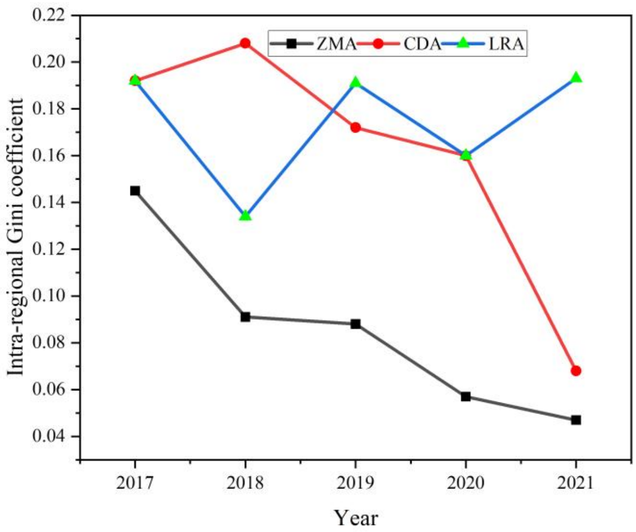

Fig.9. Trends in the Gini Coefficient within Intra-Regional

Inter-regional analysis revealed that the Gini coefficient of TESTA among regions exhibited a U-shaped pattern, initially declining and subsequently rising (see Fig. 10).

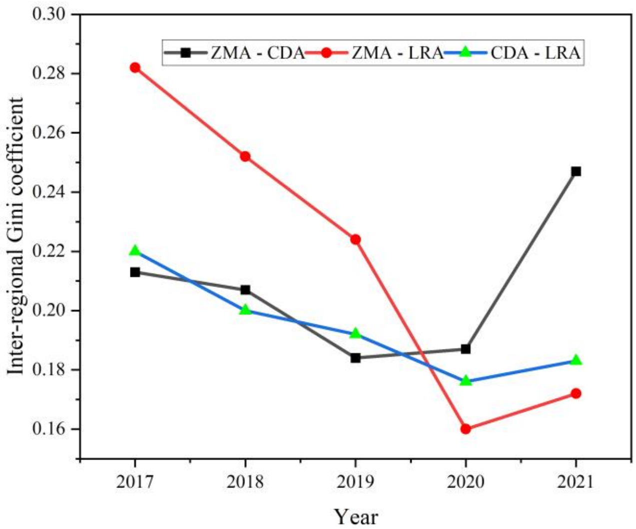

Fig.10: Trends in the Gini Coefficient within Inter-Regional

Considering the average inter-regional differences from 2017 to 2021, the ranking was ZMA–LRA (0.218) > ZMA–CDA (0.208) > CDA–LRA (0.194). Specifically, the ZMA–CDA coefficient increased from 0.213 in 2017 to 0.247 in 2021, representing a 16% rise. Conversely, the Gini coefficient between the ZMA and LRA decreased from 0.282 to 0.172 over the same period, a reduction of 39%, indicating a substantial narrowing of the development gap between these regions. The CDA–LRA coefficient experienced a smaller decline, decreasing from 0.220 in 2017 to 0.183 in 2021, corresponding to a 17% reduction.

From the perspective of source contribution rates across the three regions (see Fig. 11), both intra-regional contributions and super-variable density contributions exhibited a general downward trend from 2017 to 2021, while inter-regional contributions increased markedly. Over the sample period, intra-regional, inter-regional, and super-variable density contribution rates ranged between 21%–29%, 41%–64%, and 15%–30%, respectively. Considering the overall averages, inter-regional contributions (47.798%) exceeded intra-regional (27.342%) and super-variable density contributions (24.860%). These findings indicate that disparities in TSTA development within Henan Province are predominantly driven by inter-regional differences. Factors such as uneven economic foundations, policy support, innovation capacity, human capital, and infrastructure contribute to these gaps. To mitigate regional disparities and promote coordinated, balanced development of TSTA, priority should be given to reducing differences between regions, particularly the development gap between the ZMA and LRA.

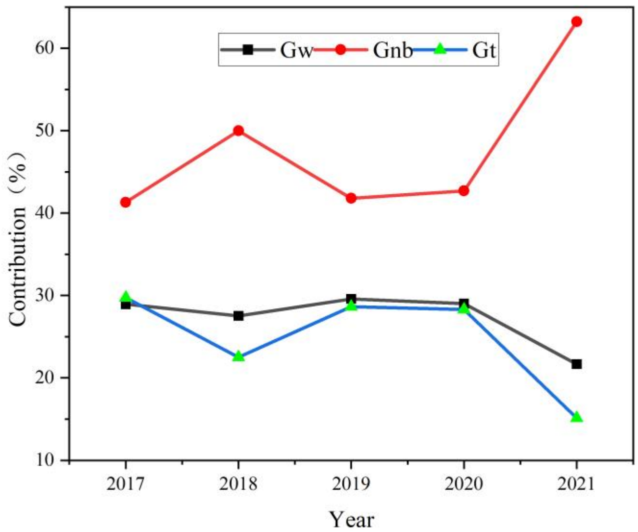

Fig.11: Sources of Regional Differences and Contribution Rates

4. Discussion and Limitations

4.1 Discussion

Enhancing TESTA represents a critical mechanism for driving innovation-led development. TSTA serves as a primary conduit for translating scientific research outputs into tangible productivity, thereby fostering economic growth and social advancement. High-efficiency TSTA strengthens firms' competitive capabilities while simultaneously facilitating industrial transformation and promoting a more optimised economic structure.

A review of existing research indicates that no comprehensive, systematic investigation of TESTA has been conducted at the city level within Henan Province. Given its role as a key economic hub in central China, examining TESTA in Henan is essential for regional development. This study addresses this gap, providing targeted analysis and policy recommendations for TSTA. Unlike prior literature Li and Zhang [14], the present study utilises a three-stage DEA model to conduct a static assessment of TESTA, eliminating environmental factors and random disturbances to more accurately reflect the actual performance of each city. Building on reference Shuai and Fan [15], the MI model is further employed to conduct a dynamic analysis, capturing temporal trends in efficiency and evaluating the contributions of Tech and Effch to TESTA. This approach allows for both horizontal and vertical comparisons, offering a multidimensional perspective that elucidates the current status, challenges, and development trajectories of TESTA across cities in Henan Province.

Following the isolation of environmental factors and stochastic disturbances via the SFA regression model, results demonstrate that government financial support, scientific research atmosphere, and regional economic development significantly influence the slack variables of input indicators. Consequently, the necessity of adjusting for these factors is confirmed. Post-adjustment, TESTA across cities declines compared with first-stage results, with SE, rather than PTE, identified as the principal determinant of regional efficiency. Adjusted TE continues to follow the hierarchy ZMA > CDA > LRA. Analysis using the adjusted MI model reveals that Tfp and Tech exhibit parallel fluctuation patterns, indicating that improvements in Tfp from 2017 to 2021 are primarily driven by technological progress. Dagum Gini coefficient analysis shows that, despite an overall downward trend, both intraand inter-regional disparities remain substantial, with inter-regional differences—particularly between ZMA and LRA—constituting the major source of inequality.

From a management perspective, the integrated three-stage DEA–MI–Dagum framework highlights the significant roles of environmental factors, SE, Tech, and regional disparities in shaping TESTA. The analysis provides empirical evidence and managerial insights for innovation governance. Overestimation of TESTA is predominantly attributable to environmental factors and SE, emphasising that management should prioritise optimising scale operations and resource allocation rather than solely increasing investment. The methodology has broader applicability beyond Henan Province, supporting more effective utilisation of TESTA and resources to promote sustainable, innovation-driven development, and offering strategic guidance across multiple administrative and research levels.

4.2 Limitations and Future Research Directions

Nonetheless, this study has several limitations that warrant consideration in future research. First, the temporal coverage of the data spans only five years, and the sample size is relatively small. Subsequent studies could benefit from longer data cycles and expanded samples to enhance the robustness of the analysis. Second, the current model is constrained by the characteristic that DMU efficiency values are capped at 1, without distinguishing between varying effective states of DMUs. Future research could explore integrating enhanced DEA frameworks to differentiate DMUs more precisely and identify gradations within effective states. Third, subsequent studies might incorporate spatial correlation analyses to examine how TESTA development interacts across different regions. Since the environmental variables employed in the present SFA model have not been standardised, future investigations should consider evaluating changes in these variables pre- and post-standardisation and conducting comparative analyses. Finally, a comparative perspective involving other provinces or international cases could provide a more comprehensive evaluation of Henan's TESTA performance, offering broader insights into regional innovation practices.

5. Conclusion and Policy Recommendation

5.1 Conclusion

This study utilises the 2017–2021 period as its sample, drawing on prior research to establish a rigorous and systematic evaluation framework for TESTA. The three-stage DEA–MI model is employed to assess TESTA in Henan Province, while regional disparities are examined through the Dagum Gini coefficient decomposition method. The empirical findings indicate that the enhancement of TESTA in Henan Province is constrained by three primary challenges: scale diseconomy, dependence on external technological progress, and pronounced regional imbalances. Consequently, policy interventions must adopt targeted and differentiated strategies. First, to mitigate inadequate SE, policies should focus on integrating innovation resources, fostering collaboration among innovation entities, and promoting the development of innovation clusters to realise scale economies. Second, to reduce reliance on external Tech, efforts should strengthen support for original innovation and breakthroughs in independent core technologies while maintaining R&D investment, thereby cultivating sustainable technological innovation capabilities. Third, to address pronounced regional efficiency disparities, region-specific coordination strategies should be implemented to narrow development gaps and advance the overall level of TESTA. The following section outlines concrete policy recommendations.

5.2 Policy Recommendation

5.2.1 Optimising the Scale Effect is a Crucial Approach to Improving TESTA

SE constitutes the principal constraint on the advancement of TESTA in Henan Province. To achieve sustainable development, it is essential to encourage high-tech enterprises to expand their operational scale and to foster industrial agglomeration alongside collaborative innovation. Government support should prioritize high-tech enterprises, particularly small, medium, and micro-sized firms, through targeted policies such as financial subsidies and tax incentives. For enterprises that have attained a substantial scale, additional financial mechanisms, including low-interest loans or enhanced fiscal incentives, should be provided to alleviate funding constraints and further realize SE gains. Within the ZMA, CDA, and LRA, specialized industrial parks should be established to facilitate the integration of upstream and downstream industrial chains and to cultivate industrial cluster effects. Concurrently, cross-regional industrial alliances and technology trading platforms should be developed to promote technical exchanges and cooperative innovation among enterprises, jointly addressing critical technological challenges and enhancing sector-wide competitiveness. Moreover, social capital should be actively mobilized through mechanisms such as venture capital funds and VC firms, attracting private investment into the scientific and technological innovation sector, thereby creating essential financing channels for start-ups and growth-oriented enterprises and supporting rapid expansion.

5.2.2 Strengthening Technological Progress as an Endogenous Driver

The growth of Tfp in Henan Province during 2017–2021 is predominantly driven by Tech. Enhancing the contribution of Tech is therefore strategically critical for the sustainable development of cities in Henan. First, investment in scientific research should be increased, with particular emphasis on supporting basic research. Dedicated funds should be allocated from the science and technology budget, and a frontier technology exploration fund should be established to support high-risk, high-return projects. This would enable researchers to conduct original and disruptive studies, with mechanisms in place to tolerate and exempt failures, thereby fostering a robust source of vitality for Tech. Annual increases in funding for basic scientific research should be ensured to maintain steady growth, while optimising the allocation of scientific resources to prevent duplication and waste, focusing on addressing major scientific and technological challenges constraining development in Henan and nationally.

Second, research institutions should reform professional title evaluation and performance assessment systems. Market-oriented evaluation indicators, such as the transaction value of technology contracts and equity investments linked to achievements, should be accorded equal or greater importance than academic publications and project outputs. This would guide researchers to prioritise problem-solving and the generation of tangible outcomes over mere paper production. Third, the independent development and recruitment of high-end talent should be strengthened. Policies should be designed to attract top scientists and research teams from both domestic and international sources, enriching the local talent pool. Simultaneously, local talent development should be intensified, with particular attention to enhancing the capabilities of young researchers. Creating a conducive career environment will ensure that talent is effectively attracted, retained, and utilised.

5.2.3 Enhance Regional Development Coordination While Bridging Regional Gaps

Henan Province exhibits complex geographic conditions and pronounced disparities in economic development, particularly between the ZMA and the LRA. To achieve high-quality economic growth, differentiated regional strategies should be adopted. First, the ZMA should serve as the core driver. As the province's centre for scientific and technological innovation, the ZMA can demonstrate best practices in R&D, industrial upgrading, and related activities. Policies that prioritise the ZMA and promote resource sharing will stimulate coordinated growth in adjacent cities, forming a "1+8" pattern for the greater ZMA. Second, the technological application and innovation capacity of the CDA require targeted attention. For cities exhibiting low Tech efficiency, government agencies and relevant departments should conduct in-depth analyses to identify root causes. Establishing external expert advisory groups to provide technical guidance and support to local enterprises can help overcome technical bottlenecks and improve production efficiency. Third, the LRA should focus on the development of region-specific industries. Leveraging local natural resources and development potential, industrial layouts should be planned according to local conditions, including initiatives such as agricultural deep processing and eco-tourism. The full utilisation of national support policies for central and western regions, combined with active pursuit of national projects, can inject new vitality into local economic and social development.

6. Funding

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