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Evaluation of Innovation Performance of Logistics Enterprises Based on DEA Model

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Abstract: *With the deepening of global economic integration and the rapid growth of e-commerce, innovation has become a key driver for Chinese logistics enterprises to enhance competitiveness and modernize operations. This paper analyzes 48 listed logistics enterprises in China from 2015 to 2023, using R&D expenditure, R&D personnel, and total fixed assets as input indicators, and patent applications and intangible asset growth as output indicators, measured by a single-stage SBM-DEA model. The results show that overall innovation performance is relatively low, with a mean of 0.2123, significant structural differences exist, and performance fluctuates without a consistent upward trend. Recommendations are proposed to optimize innovation resource allocation and improve overall performance.*

Keywords: *Logistics Enterprises, Innovation performance, DEA Model, SBM Model*

1. Introduction

With the deepening of global economic integration and the rapid development of e-commerce, China logistics industry has achieved remarkable achievements in recent years. According to the latest data released by the China Federation of Logistics and Purchasing (CFLP), the total revenue of China logistics industry reached 13.8 trillion yuan in 2024, a year-on-year increase of 4.9%. This trend indicates that China logistics industry continues to demonstrate strong resilience and development potentia. At the enterprise level, the total operating income of China top 50 logistics enterprises exceeded 2.1 trillion yuan, highlighting the leading role and competitive advantages of leading enterprises in the market. As an important pillar industry of the national economy, the logistics industry is increasingly becoming a new engine driving economic growth, playing a key role in promoting industrial structure optimization, accelerating the transformation of development modes and enhancing national competitiveness[1] . Furthermore, Yan also points out that the high-quality development of the logistics industry has a positive promoting effect on the high-quality development of the national economy[2].

The wide application of emerging technologies such as big data, the Internet of Things and artificial intelligence is accelerating the development of the logistics industry towards intellectualization and informatization. In this context, the R&D and innovation capability of enterprises has become a core factor determining their market competitive position. Therefore, constructing a scientific and systematic evaluation system for the innovation performance of logistics enterprises is of great significance for the high-quality and sustainable development of the industry. Existing studies generally believe that the "innovation performance" of enterprises is an important indicator to measure the effectiveness of innovation activities. It mainly measures whether enterprises can transform the input of innovation resources such as capital, human resources and technology into valuable outputs such as patents, new services or process optimization[3]. In addition, studies have shown that although enterprise performance is usually used as a dependent variable in empirical research, innovation performance can be used as an mediating variable between business processes and overall performance, thus revealing the internal operation mechanism and effectiveness of enterprises more deeply[4]. However, when exploring the input-output relationship of logistics innovation, existing studies mostly focus on qualitative evaluation or single indicator measurement, and there is still a lack of in-depth research on the innovation performance at the enterprise level, particularly in assessing the relative efficiency of innovation activities under resource constraints.

This paper selects 48 listed logistics enterprises in China as research samples, uses the single-stage Slack-Based Measure (SBM) model to assess and compare the innovation efficiency of enterprises, and reveals the actual level and main differences of innovation activities of logistics enterprises in China from an empirical perspective. With the help of the SBM model, the input redundancy and output deficiency can be identified more accurately, thus providing a more precise quantitative basis for understanding the formation mechanism of innovation performance of logistics enterprises.

2. Literature Review

2.1 The Meaning and Measurement of Innovation Performance

Innovation performance is an important indicator to measure the achievements of enterprises in innovation activities, referring to the comprehensive embodiment of technological progress, performance improvement and market value growth realized by enterprises through innovation activities[5]. Alegre et al. and other scholars systematically conceptualized and operationalized the definition of innovation performance, pointing out that innovation performance should include two core dimensions: "effectiveness" and "efficiency"[4]. Among them, effectiveness mainly reflects whether innovation achievements are in line with the strategic development goals of enterprises, while performance focuses on the rationality of resource use in the innovation process. This two-dimensional perspective has provided a solid theoretical tool and empirical basis for subsequent research, and has had a far-reaching impact on the field of innovation performance research. On this basis, Cruz-Cázares further proved through empirical research that innovation performance serves as an effective measure of technological innovation outcomes[6].Various quantitative methods have been adopted to measure innovation performance in existing research, including factor analysis and stochastic frontier approach (SFA), yet these methods have notable practical limitations. By contrast, Data Envelopment Analysis (DEA), a non-parametric method, constructs a performance frontier for multi-input and multi-output via linear programming, which can effectively evaluate the relative innovation performance of each decision-making unit (DMU)[7]. Since its initial proposal by Afriat and Charnes, DEA has become a key tool for non-parametric performance evaluation[3,7].

2.2 Application of DEA Model in Innovation performance Evaluation

Existing literature on innovation performance using the DEA method cover three levels: regional, industrial and enterprise.At the regional level, Jovanović evaluated the innovation performance of 34 OECD countries using the DEA model within the triple helix framework[8]; Liu used the two-stage DEA method to evaluate the R&D performance of industrial enterprises in 30 provinces of Chinese mainland, revealing the unbalanced problem of resource allocation among regions[9]; Du et al. used the DEA-BCC model to evaluate the innovation performance of manufacturing industry in Wuhan Urban Agglomeration[10]; Yesilay et al. used the CRS model to evaluate the innovation performance of countries in the European Economic Community[11]. In terms of industrial research, Li et al. used the three-stage DEA model to measure the innovation performance of the semiconductor industry in China, targeting technical performance, scale performance and pure technical performance respectively[12]; Wang et al. used the CCR model to study the technological innovation performance of 18 high-tech industries in China[13]. At the enterprise level, Lan used the three-stage DEA model to measure the innovation performance of China photovoltaic enterprises[14]; Xiang et al. evaluated the innovation performance of 24 listed companies in development zones of Hubei Province from 2012 to 2017[15]; Guan et al. used the traditional DEA model to analyze the innovation capability of 182 industrial enterprises in Beijing[16].Overall, compared with other methods, DEA provides greater discriminatory power in performance evaluation and stronger comparability. Due to its non-parametric nature, its ability to handle multi-dimensional inputs and outputs, and its capacity to directly identify sources of performance loss, DEA is particularly suitable for measuring and comparing the innovation performance of logistics enterprises.

2.3 Research Status of Logistics Enterprise Innovation performance Based on DEA

Given the extensive application of the DEA method in manufacturing, regional innovation systems, and high-tech industries, scholars have gradually introduced the performance perspective into the logistics industry in recent years. Kim & Shin used the combination of DEA and Kruskal Wallis one-way ANOVA to measure the innovation performance of 72 Korean logistics enterprises[17]; Zhou et al. evaluated the innovation performance of 49 listed logistics enterprises through a three-stage model, and revealed the joint impact of environmental variables and management factors on DEA results combined with the SFA model[18].In general, although existing studies provide important references for the evaluation of innovation performance of logistics enterprises, there are still deficiencies in limited sample size, scattered model types, as well as the construction of evaluation indicators, sources of inefficiency and model simplicity.

3. Methodology

3.1 DEA-SBM Model

Since the process of technological innovation of logistics enterprises is a complex and long-term process, involving multiple input and output variables, this paper decides to choose the data envelopment analysis method.

DEA is based on linear programming and using the distance function to evaluate the performance of DMUs. There are two traditional DEA models: one is the CCR model based on constant returns to scale, and the other is the BCC model based on variable returns to scale. These two models are also radial, requiring the input and output to be enlarged or reduced in the same proportion. If there are slack inputs or outputs, the performance value will be overestimated. To this end, Tone proposed the SBM model in 2009, which solved the problem of slack variables[19]. This model seeks to minimize the average proportional excess in input use (represented by slack variables) relative to the observed inputs, thereby identifying the potential for performance improvement. It can avoid the bias caused by radial measurement and better reflect the inperformance.

Assume that there exist n decision making units (DMUs). Each DMU use m inputs to generate g outputs. The input and output matrices are expressed as $X=(x_{ij})\in R^{m\times n}$ and $Y=(y_{rj})\in R^{r\times n}$. The production possibility set P can be defined as

$$P=\{(x,y)|x\geq X\lambda,|y\leq Y\lambda,\lambda\geq 0\} \tag{1}$$

Where λ is a non-negative weight vector, representing the intensity of each DMU in constructing the optimal production frontier.

Based on Tone (2001), the non-oriented VRS SBM model is the following model (2).

$$\begin{aligned}
&\rho_o^{SBM}=\min\frac{1-\frac{1}{m}\left(\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}\right)}{1+\frac{1}{g}\left(\sum_{r=1}^{g}\frac{s_r^+}{y_{ro}}\right)}\\
&s.t.\quad X\lambda+s^-=x_o,\\
&\qquad Y\lambda-s^+=y_o,\\
&\qquad e\lambda=1,\\
&\qquad \lambda,s^-,s^+\geq 0.
\end{aligned} \tag{2}$$

where s^- and s^+ are slack variables of inputs and outputs. The subscript o denotes the evaluated DMU. The objective value ρ_o^{SBM} denotes the performance for the evaluated DMU, ranging from 0 and 1. It will be evaluated efficient when an optimized solution contains neither redundant inputs nor insufficient outputs, i.e. $\rho_o^{SBM}=1$. , If the constraint $e\lambda=1$ is deleted, the CRS setting of the SBM model can be obtained.

3.2 Indicator Selection

In the research on innovation performance, the selection of input and output indicators is usually based on the classic "input-output" theoretical framework of innovation activities. In existing literature on the measurement of enterprise innovation performance, innovation inputs are mostly considered in terms of R&D and capital investment, and innovation outputs in terms of technological outputs and knowledge capital accumulation. Specifically, R&D expenditure and the number of R&D personnel are widely used to measure the level of enterprise innovation input, and fixed assets or capital stock are often used as the material basis to support innovation activities; in terms of output, patent applications, intangible assets or technological achievement transformation indicators are generally used to reflect enterprise innovation output and value realization[3,5,19]. Based on the common practices of existing studies, combined with the industrial characteristics of innovation activities of logistics enterprises and

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the availability of sample data, this paper selects R&D expenditure, the number of R&D personnel and total fixed assets as innovation input indicators, and patent applications and the increase in intangible assets as innovation output indicators.

4. Empirical Analysis

4.1 Sample and Data Source

The data used in this study are primarily drawn from the CSMAR Database and the annual reports of Chinese A-share listed companies. Panel data for 62 logistics enterprises from 2010 to 2023 were compiled. Due to missing data or insufficient continuity, 48 listed logistics enterprises with complete and consistent data were ultimately selected, resulting in 247 firm-year observations.

Table 1: Descriptive statistics of input and output variables

	AVERAGE	STDEV	MAX	MIN
Fixed Assets (10,000 yuan)	760207.72	952695.35	4568149.69	5534.93
Increase in Intangible Assets (10,000 yuan)	104230.31	299512.40	2152906.48	1.90
R&D Investment (10,000 yuan)	14382.51	42144.69	313118.98	45.07
R&D Personnel (Person)	456.98	877.27	6271	3
Number of Patent Applications (Piece)	49.79	97.47	777	1

To examine the impact of business types and geographical distribution on R&D performance, the sample covers various segments, including warehousing, port operations, express delivery, road transportation, and integrated logistics services. These enterprises are distributed across eastern, central, and western regions of China, enabling a comprehensive reflection of differences in innovation performance across different stages of regional development. In addition, the sample includes several leading and representative enterprises, such as SF Holding Co., Ltd., Zhejiang Materials Industry Group Co., Ltd., and Yunda Express Co., Ltd., which have high market shares and strong innovation activity in their respective segments, thereby enhancing the external validity of the results. Table 1 presents descriptive statistics for the main input and output variables.

4.2 Overall Performance

Figure 1 presents the distribution of innovation performance scores for 247 logistics enterprises based on DEA results.

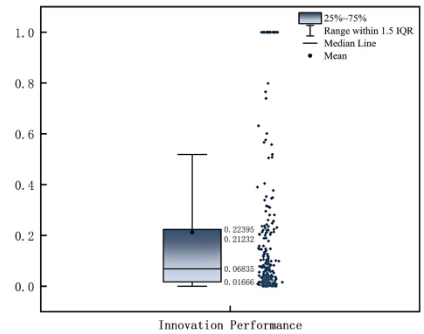

Figure 1: Innovation Performance Distribution

In terms of the overall level, the mean innovation performance of the sample enterprises is only 0.2123, while the median is 0.06835. Both are far lower than the ideal DEA value of 1, indicating that overall innovation efficiency remains at a low level. The median is substantially lower than the mean, suggesting a distribution skewed toward low-performance outcomes, with the mean being pulled upward by a small number of high-performing enterprises. This indicates that most logistics enterprises suffer from low efficiency in transforming innovation inputs into outputs, and the potential of innovation activities has not been fully exploited. In terms of distribution characteristics, the first

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quartile (Q1) is 0.01666 and the third quartile (Q3) is 0.22395, indicating that the distribution is concentrated in the low-performance range. Combined with the scatter distribution, most observations fall within the 0–0.2 interval, revealing a clear pattern of low-level agglomeration. This suggests that the overall foundation of innovation capacity in the logistics industry remains relatively weak. Meanwhile, the upper whisker of the box plot is relatively long, and several high-value outliers are observed. The innovation performance of some enterprises is significantly higher than the industry average, with a few even approaching the DEA efficiency frontier. This indicates that a small number of enterprises possess strong capabilities in integrating innovation resources. However, such enterprises are limited in number, resulting in a substantial gap between high- and low-performing firms and widening the overall performance disparity. This reflects that China's logistics industry is still in a transitional upgrading stage, and a widely efficient innovation system has not yet been established.

4.3 Innovation Performance of Enterprises by Business Type

Based on the Shenyin & Wanguo Industry Classification (2021 Revision), the sample is divided into seven main business categories, including warehousing, port operations, road freight transport, express delivery, cross-border logistics, raw material supply chain services, and intermediate and consumer goods supply chain services. Table 2 reports the innovation performance scores for the seven categories of logistics enterprises.

Table 2: Innovation performance of different business types of logistics enterprises

Business Type	Number of Enterprises	Innovation Performance
Warehousing Logistics	5	0.1238
Port Operation	13	0.2475
Road Freight	5	0.1612
Express Delivery	5	0.3279
Cross-border Logistics	9	0.1903
Raw Material Supply Chain Services	5	0.2782
Intermediate and Consumer Goods Supply Chain Services	6	0.1132

The results show that express delivery enterprises achieve the highest innovation performance, reaching 0.3279 and significantly outperforming other categories. Raw material supply chain service enterprises follow with an innovation performance of 0.2782. Port operation enterprises record an innovation performance of 0.2475. In contrast, cross-border logistics enterprises show relatively low innovation performance (0.1903), likely constrained by institutional and procedural complexities. Road freight enterprises also perform poorly (0.1612). Warehousing enterprises exhibit similarly low innovation performance (0.1232). Intermediate and consumer goods supply chain service enterprises record the lowest innovation performance (0.1132). This may be attributed to highly diverse and volatile demand, increased coordination complexity, and inconsistencies in digital capabilities across supply chain participants. These factors hinder the implementation of systematic technological innovation, resulting in low overall innovation performance.

4.4 Innovation Performance of Enterprises by Geographical Location

This paper conducts a classification analysis of the innovation performance of logistics enterprises from a geospatial perspective. The geographical location of enterprises is based on their headquarters location, and divided according to the commonly used eight major economic zones in China. Table 3 shows the differences in innovation performance of logistics enterprises in different geographical locations.

Specifically, the average innovation performance of logistics enterprises in the southern coastal region is the highest, reaching 0.3559, which is significantly higher than that of other regions. The innovation performance of logistics enterprises in Northeast China and the middle reaches of the Yellow River is 0.2724 and 0.2404, respectively, representing a moderate level. In contrast, the innovation performance of the northern coastal region and the eastern coastal region is 0.1641 and 0.1491, respectively, indicating a relatively low level. The innovation performance of logistics enterprises in Southwest China is the lowest, at only 0.0232. It should be noted that the number of sample enterprises in Northeast China, Southwest China, and the middle reaches of the Yellow River is only one in each case. Therefore, the results mainly reflect firm-level characteristics and have limited regional representativeness; the corresponding conclusions should be interpreted with caution.

Table 3: Innovation performance of logistics enterprises in different geographical locations

Geographical Location	Number of Enterprises	Innovation Performance
Southern Coastal Area	16	0.3559
Northern Coastal Area	11	0.1641
Eastern Coastal Area	18	0.1491
Southwest China	1	0.0232
Northeast China	1	0.2724
Middle Reaches of the Yellow River	1	0.2404

5. Conclusions and Recommendations

5.1 Research Conclusions

The overall innovation performance of China's logistics enterprises is relatively low, with an average value of only 0.2123. Since the median is much lower than the mean, the sample is skewed toward low performance, meaning most firms struggle to convert innovation inputs into effective outputs. Significant structural differences also exist: by business type, express delivery enterprises achieve the highest innovation performance, while intermediate and consumer goods supply chain services and warehousing logistics rank the lowest. Geographically, enterprises in southern coastal areas outperform those in other regions, presenting obvious regional agglomeration.

5.2 Policy Recommendations

To address the low R&D performance and uneven innovation levels of logistics enterprises, relevant measures should be taken. First, the government should establish a collaborative innovation system and strengthen innovation infrastructure by building integrated platforms that facilitate resource and information sharing among enterprises, universities and research institutes. The government should also accelerate the development of digital infrastructure and improve mechanisms that promote talent mobility and knowledge exchange. Second, industry associations should play a coordinating role by establishing innovation collaboration networks to promote the sharing of information, R&D achievements and supply chain data, while encouraging joint R&D to address common industry challenges and improving intellectual property protection and benefit distribution mechanisms. Finally, enterprises should enhance their innovation capabilities by increasing investment in digital and intelligent technologies, strengthening cooperation with universities and research institutes, and adjusting innovation strategies according to their business types, regions and development stages.

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