A Study on the Financial Performance of Chinese Artificial Intelligence Listed Companies Based on the DEA-Malmquist Model

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Abstract. This study aims to assess the financial performance of Chinese AI-listed companies. It utilizes the DEA-Malmquist model to conduct static and dynamic analysis on data from 2018 to 2022. The findings indicate that these companies generally perform well financially, with room for improvement. Technological Progress emerges as the primary driver of enhanced financial performance in the industry. While Total Factor Productivity fluctuates, it shows an overall growth trend. Based on these results, the study offers specific recommendations for enterprises and policymakers to foster the healthy development of the Chinese AI industry.

Keywords: Artificial Intelligence**,** Financial Performance, DEA, Malmqusit Index.

1. Introduction

Artificial intelligence, as a strategic technology leading the future, has become the core of international competition. Its development is expected to accelerate, thereby triggering profound changes in the field of technology and having broad and far-reaching impacts on the economy and society [1]. In 2017, the State Council issued the " Development Planning for a New Generation of Artificial Intelligence" clearly setting three strategic goals for the development of the new generation of artificial intelligence and elevating artificial intelligence to the national strategic level. The "Report on the Work of the Government 2022" emphasizes the necessity of accelerating the development of the industrial Internet, promoting the cultivation and growth of digital industries such as integrated circuits and artificial intelligence, and strengthening the innovation and supply capacity of key software and hardware technologies. The new generation of artificial intelligence has a special driving effect, which helps to promote the overall breakthrough of strategic emerging industries and is gradually becoming an important lever for building a strong manufacturing country and a strong network country [2]. Accelerating the development of the new generation of artificial intelligence is of great significance for promoting China's science and technology to achieve leapfrog development, optimizing and upgrading the industrial structure, and overall enhancing the level of productivity [3].

According to data released by the China Academy of Information and Communications Technology, the market size of China's artificial intelligence industry reached 508 billion yuan in 2022, achieving a year-on-year growth of 18%. This indicates that China's artificial intelligence industry is ushering in new development opportunities and injecting new growth momentum into the Chinese economy. However, China's current artificial intelligence industry still lags behind developed countries such as the United States in terms of technological innovation capabilities and core technologies. Chinese artificial intelligence companies are also shifting from past scale expansion to quality improvement.

Since few scholars have evaluated the financial performance of the AI industry, in view of this, we analyze the financial performance of the artificial intelligence industry in depth through the DEA-Malmquist model, which provides a new perspective for the research in this field, and also brings important insights for predicting the future development trend of the artificial intelligence industry, improving the financial management level of the enterprises, as well as promoting the growth of

China's economy, etc., so the study on the current status of the financial performance of the AI enterprises and their influencing factors has a very important practical significance.

2. Literature review

With the development of China's economy and the advancement of information technology, enterprises are facing the transformational need to introduce financial performance evaluation mechanisms. Financial performance evaluation plays a crucial role in enterprise management, so many scholars use various methods to study financial performance. Luo Wenhao et al. (2018) conducted a study using the DuPont analysis to examine the case of Midea Group's acquisition of KUKA in Germany. They found that the integration measures implemented by Midea Group had an impact on its own financial performance following the merger[4]. Wang Jing et al. (2019) conducted a study using factor analysis and DEA-BCC to evaluate the financial performance of 25 agricultural listed companies in China in 2017. They found that the overall financial performance was low, with significant differences between different sub-industries.[5]. Feng Xuebin et al. (2020) selected 15 listed companies in the agricultural and animal husbandry sectors from Shanghai and Shenzhen as their research subjects. They used the principal component analysis method to extract four main components, providing an objective evaluation reference for relevant stakeholders[6].Hou Xiangding (2021) selected financial data from 18 leading logistics supply chain companies listed on the A-share market in 2019. They constructed an index system and used factor analysis to extract common factors. The analysis revealed that these companies showed little difference in performance in terms of profitability, operations, and asset equity. As a result, they proposed policy suggestions such as strengthening cost management and enhancing resource integration capabilities[7].Hu Furai (2021) constructed a financial performance evaluation system for state-owned enterprises based on the EVA (Economic Value Added) and proposed optimization strategies to improve its application in state-owned enterprises[8].Tang Huaguo studied local universities in Guangxi, using the AHP (Analytic Hierarchy Process) to examine the financial performance evaluation indicators and weights of universities, and proposed suggestions to improve financial management performance.[9].

With the continuous development of technology, artificial intelligence technology has been widely applied across various fields. However, the artificial intelligence industry in China is still emerging. Therefore, few scholars have evaluated the financial performance of the artificial intelligence industry. Relevant studies are as follows: Ying Limeng et al. (2020) empirically analyzed the impact of intelligent manufacturing on corporate performance based on panel data of Chinese manufacturing listed companies from 2014 to 2018 using the PSM-DID method[10]. Li Qingxue (2021) selected the financial data of 61 listed companies in the intelligent manufacturing industry in 2019 as the research object and used factor analysis to comprehensively evaluate these data[11]. Jin Jiahui (2023) conducted a performance study on Company N in the intelligent warehousing and logistics industry based on the Wal-Mart scoring method and constructed a new performance evaluation system[12].

In conclusion, research on financial performance evaluation systems and methods is still ongoing, but there is relatively little research on the financial performance of the artificial intelligence industry, and even fewer studies use the DEA-Malmquist model to evaluate the financial performance of artificial intelligence listed companies. Therefore, this study takes 59 artificial intelligence listed companies on the Shanghai Stock Exchange as research samples. Based on the DEA-Malmquist model, it constructs an evaluation index system from four aspects: profitability, solvency, operational capability, and development capability. The study evaluates the financial performance of artificial intelligence listed companies from 2018 to 2022 in both static and dynamic aspects.

3. Research methodology and data sources

3.1. Data Envelopment Analysis

DEA (Data Envelopment Analysis) is a non-parametric method proposed by American operations researchers A. Charnes, W. W. Cooper, and E. Rhodes in 1978. It is developed based on the concept of relative efficiency evaluation.

In the DEA method, the evaluated objects are called DMUs (Decision-Making Units). DEA uses multiple input and output data of DMUs to establish a data envelopment curve, known as the production frontier, through linear programming. On this curve, efficient points lie on the frontier, with an efficiency value of 1, while inefficient points lie outside the frontier, with efficiency values between 0 and 1.

The DEA model is specifically divided into two types: the CCR model and the BCC model.

The CCR model is based on the assumption of constant returns to scale, which means that under a given scale, the production efficiency of DMUs remains consistent. However, in reality, technological innovation and unequal competition may cause changes in returns to scale. Some decision-making units may not be able to operate at optimal scale, which limits the applicability of the CCR model in describing certain real-life situations.

To address this issue, Banker, Charnes, and Cooper extended the DEA model in 1984, introducing the BCC model. This model addressed the limitation of the CCR model, which assumed constant returns to scale, by allowing for variable returns to scale. While the CCR model focused on TE (Total Efficiency), the BCC model further decomposed TE into PTE (Pure Technical Efficiency) and SE (Scale Efficiency). The efficiency assessment model is presented below:

$$\min\theta_k$$
$$s.t\begin{cases}\sum_{\substack{i=1\\i\neq k}}^{n} X_i\lambda_i + S_k^- = \theta_k X_k \\ \sum_{\substack{i=1\\i\neq k}}^{n} Y_i\lambda_i - S_k^+ = Y_k \\ \lambda_i \geq 0; i = 1,2,3,\dots,n \\ S_k^-, S_k^+ \geq 0\end{cases} \tag{1}$$

In the equation, $X$and$Y$represent the input and output values of DMUs, respectively; λ_i denotes the weight coefficient of the corresponding indicator; S_k^- and S_k^+ represent the slack variables of output and input, respectively; i denotes the i-th decision-making unit; n is the number of DMUs; $\theta_k$is the input-output efficiency value of the k-th decision-making unit, which can be used to determine the effectiveness of the DEA model.When $\theta = 1.000$, the DEA is effective;if $\theta < 1.000$, it indicates redundancy or insufficiency, resulting in ineffective DMUs.

There exists the following relationship among TE, PTE, and SE:

$$\theta_{TE} = \theta_{PTE} \times \theta_{SE} \tag{2}$$

TE indicates the production efficiency of decision-making units at their optimal scale, measuring their capabilities in resource allocation and utilization efficiency.When $\theta_{TE} = 1$, it signifies that the unit has achieved optimal relative efficiency with a rational input-output structure. PTE reflects the impact of management and technical factors on production efficiency.$\theta_{PTE} = 1$ indicates that input factors are fully utilized to maximize output under a specific input combination. SE demonstrates the influence of scale factors on production efficiency. $\theta_{SE} = 1$ suggests effective scale efficiency (constant returns to scale), indicating the attainment of the optimal scale.

3.2. Malmquist productivity index

The Malmquist productivity index method, first introduced by Swedish economist and statistician Malmquist.S in 1953, offers a valuable tool for analyzing Tfpch（Total factor productivity change) in the AI industry. While the BCC model is limited to static analysis of data indicators at specific points in time, the Malmquist productivity index method can overcome this limitation, allowing for the analysis and comparison of efficiency changes in Decision-Making Units across different periods.

Tfpch is decomposed into Techch (Technical change) and Effch (Efficiency change), which are calculated using the following formula:

$$\text{Tfpch} = \text{Techch} \times \text{Effch} = \sqrt{\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D^t\left(x^t, y^t\right)}{D^{t+1}\left(x^t, y^t\right)}} \times \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)} \tag{3}$$

In the equation, Tfpch is decomposed into Techch and Effch, which are calculated using the following formula:

x^tandy^trepresent the inputs and outputs for period t,respectively,and x^{t+1}andy^{t+1}represent the inputs and outputs for period $t+1$,respectively. $D^t\left(x^{t+1}, y^{t+1}\right)$, $D^{t+1}\left(x^t, y^t\right)$ represents the distance of inputs and outputs for period $t+1$ relative to the production frontier for periods t and $t+1$. $\sqrt{\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D^t\left(x^t, y^t\right)}{D^{t+1}\left(x^t, y^t\right)}}$ represents the Techch,and $\frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)}$ represents Effch, which can be further decomposed into the product of Pech（Pure technical efficiency change) and the Sech (Scale efficiency change).

In summary, Tfpch is derived as the product of Techch, Pech and Sech. The formula is as follows:

$$\text{Tfpch} = \text{Techch} \times \text{Effch} = \text{Teach} \times \text{Pech} \times \text{Sech} \tag{4}$$

If $Tfpch > 1$, it indicates an increase in the total production factors from period t to $t+1$; otherwise, it indicates a decrease. This measure evaluates the comprehensive productivity of various factors in the industry units. Techch represents the change in technological level from period t to $t+1$. Pech measures the impact of resource management factors on production efficiency, reflecting the ability to use resources efficiently and optimally, i.e., the ability to achieve the optimal allocation ratio of resource inputs. Sech reflects the impact of increasing production scale on production efficiency[13].

3.3. Data Sources

As the artificial intelligence industry has been developing rapidly in recent years, selecting the data of the last five years can better reflect the latest trends and changes in the industry, therefore, the samples of this research are selected from the companies in the Artificial Intelligence Concept Stocks sector of Straight flush listed on the Shanghai Stock Exchange from 2018 to 2022, and in the process of selecting the research samples, the companies that have incomplete data required, have large fluctuations in operating performance, and are currently or have been in a ST or *ST position in the last five years are eliminated. ST or *ST companies within five years, and finally selected 59 AI listed companies as research objects, with raw financial index data from the CSMAR database.

3.4. Dimensionless normalization

Dimensionless normalization,also referred to as data standardization or normalization,is employed to eliminate incomparability between different indicators due to dimensional differences. In this study, since we used DEAP2.1 software to process the data, the software could not calculate the data with 0, so we added 0.1 after the formula, which did not affect the final result. Thus, we normalized the original data, and the specific calculation process is as follows:

$$X_{ij}^{'} = \frac{X_{ij} - \min\left(X_j\right)}{\max\left(X_j\right) - \min\left(X_j\right)} + 0.1 \tag{5}$$

X'_{ij}represents the j−th indicator of the i−th company,min (X_j) represents the maximum value of the j-th indicator, and min (X_j) represents the minimum value of the j-th indicator.

3.5. Selection of indicators

The "Detailed Rules for Performance Evaluation of Enterprises (Revised)" issued by the Ministry of Finance of China in 2002 requires that the evaluation of non-financial companies' financial performance should cover four dimensions: debt-paying ability, operating capability, profitability, and development capability. Based on this, and combined with previous research[14], this study made corresponding adjustments and ultimately selected 10 indicators, as shown in the table1 below:

Table 1 Selected Indicator System for Financial Performance Evaluation of Artificial Intelligence Listed Companies

Category	Indicator		Calculation Method
Input indicators	Solvency	Current ratio	Current assets/current liabilities
		Quick ratio	(Current Assets - Inventories) / Current Liabilities
		Gearing ratio	Total liabilities/total assets
	Operating Ability	Total Assets Turnover Ratio	Operating Income/Total Assets Closing Balance
		Current Assets Turnover Ratio	Operating Income/Current Assets Closing Balance
Output indicators	Profitability	Return on assets	(Total profit + finance costs)/Total assets
		Net profit margin on total assets	Net Assets/Total Assets Balance
		Return on Net Assets	Net Profit/Stockholders' Equity Balance
	Development Capacity	Total Assets Growth Rate	Growth in total assets for the year / total assets at the beginning of the year
		Operating Income Growth Rate	(Total operating income of the current year - Total operating income of the previous year) / Total operating income of the previous year

4. Empirical Analysis

4.1. Static Efficiency Analysis of Listed Companies in the Artificial Intelligence Industry from 2018 to 2022

Based on the DEA-BCC model and using DEAP2.1 software, we conducted a static efficiency analysis of the input-output data of 59 listed artificial intelligence companies from 2018 to 2022. By averaging the data of TE (Total Efficiency), PTE (Pure Technical Efficiency), and SE (Scale Efficiency) over five years, we obtained the operational efficiency estimation results of artificial intelligence listed companies from 2018 to 2022, as shown in Table 2.

Table 2 DEA Estimation Results of Operational Efficiency for Listed Artificial Intelligence Companies

Listed Companies	Crste	Vrste	Scale	Crste	Vrste	Scale	Crste
SH600100	0.8176	0.9548	0.857	SH603015	0.7872	0.8312	0.948
SH600229	0.886	0.9006	0.9848	SH603018	0.9914	0.9936	0.9978
SH600271	0.831	0.91	0.92	SH603019	0.7776	0.8106	0.9648
SH600282	0.9738	0.975	0.9986	SH603038	0.7914	0.8274	0.9546
SH600288	0.7894	0.8754	0.9036	SH603066	0.9276	0.944	0.9828
SH600345	1	1	1	SH603108	0.8744	0.8858	0.987
SH600355	0.7566	0.9682	0.7776	SH603160	0.8942	0.9266	0.962
SH600410	0.758	0.923	0.8218	SH603189	0.9154	0.9638	0.9514
SH600446	0.7298	0.803	0.9088	SH603377	1	1	1
SH600498	0.8212	0.8518	0.9626	SH603486	0.9632	0.9846	0.977
SH600570	1	1	1	SH603496	0.901	0.9086	0.9918
SH600571	0.74	0.8132	0.9034	SH603528	0.8562	0.8866	0.9654
SH600582	0.7938	0.8132	0.976	SH603533	0.772	0.7856	0.9826
SH600629	0.926	0.9466	0.9772	SH603598	0.5664	0.7566	0.7312
SH600633	0.9222	0.9448	0.9746	SH603636	0.9902	0.9918	0.9984
SH600636	0.959	0.9636	0.9944	SH603656	0.8014	0.8158	0.9822
SH600637	0.916	0.9398	0.9748	SH603660	0.711	0.8022	0.8796
SH600658	1	1	1	SH603666	0.999	1	0.999
SH600718	0.9036	0.9646	0.9364	SH603679	0.8138	0.8672	0.9386
SH600728	0.8592	0.9114	0.9404	SH603686	0.7858	0.8012	0.9816
SH600751	0.762	0.8866	0.8484	SH603690	0.9956	0.9974	0.9982
SH600770	0.9906	1	0.9906	SH603716	0.7868	0.852	0.919
SH600797	0.8148	0.9028	0.9054	SH603777	0.7418	0.8262	0.8998
SH600839	0.7832	0.8692	0.9026	SH603860	0.9752	0.977	0.9982
SH600850	0.8366	0.85	0.9846	SH603869	0.9416	0.9762	0.9646
SH600967	0.9504	0.968	0.9816	SH603888	0.7922	0.8056	0.9836
SH600977	0.8532	0.8726	0.9764	SH603918	0.8218	0.8506	0.9658
SH601138	0.805	0.8514	0.951	SH603986	1	1	1
SH601360	0.9236	0.9396	0.9816	SH603990	0.9854	0.9856	0.9998
SH603000	0.9066	0.9362	0.9702	mean	0.8672	0.9084	0.9528

From the overall average perspective, the average pure technical and scale efficiencies of the 59 listed artificial intelligence companies are 0.9084 and 0.9528 respectively, with a TE value of 0.8672. This indicates that, overall, although these companies have not fully utilized their capital efficiently, their efficiency is close to 1, showing a promising development trend. In the efficiency evaluation, 5 companies have a TE value of 1, accounting for 8.5% of the total sample, demonstrating relative efficiency and indicating that these 5 companies have relatively optimal capital allocation and utilization efficiency. Among the remaining companies, SH600770 and SH603666 have achieved PTE value of 1, but their SE is inefficient. Additionally, 52 companies have not achieved either SE value of 1 or PTE value of 1, with their TE mostly between 0.7 and 1, accounting for 88.1% of the total sample. SH603598 is the only company with a TE lower than 0.7, indicating that there are still issues of unreasonable capital allocation and low capital efficiency in listed artificial intelligence companies. However, the companies' financial resource allocation and efficiency levels are relatively good.

From the analysis of TE, since the 5 companies with a TE value of 1 are relatively optimal, with appropriate input-output ratios and no need for further improvement, we will not elaborate further on them. The other 54 companies need to improve either their efficiency or input scale to achieve an optimal state. Companies with a TE below 0.75 include SH600446, SH600571, SH603598, SH603660, and SH603777, among which SH603598 has the lowest TE value of 0.5664. This is mainly due to its low PTE and SE. To achieve relative optimization, it needs to increase investment in pure technology and scale.

From the analysis of PTE, the overall performance is relatively good, with an average of 0.9084. Among them, 7 companies have achieved an efficiency of 1, accounting for 11.9% of the total sample. The two companies with the lowest PTE are SH603533 and SH603598, both below 0.8. From the above analysis, it can be seen that although some companies in the artificial intelligence industry need to improve their financial resource utilization, the financial efficiency of most companies is good. Among the 54 non-DEA efficient companies, SH600770 and SH603666 have achieved PTE value of 1, indicating that the financial efficiency of these two companies is relatively optimal, and they only need to adjust the scale of financial investment to increase output. The remaining 52 companies need to improve their technical level and increase their investment scale to achieve relative optimization.

From the analysis of SE, the overall performance is the most outstanding, with an average of 0.9528. Among them, 5 companies have achieved SE value of 1, accounting for 8.5% of the total sample. Although the number of samples that achieve SE value of 1 is not as many as those that achieve technical efficiency, among the non-scale efficient units, except for 7 companies (SH600100, SH600355, SH600410, SH600751, SH603598, SH603660, and SH603777), the SE of the remaining listed companies remains at a high level above 0.9. Among them, SH603990 and SH603666 are very close to the SE value of 1, and the SE of the decision-making unit has little effect on the company's overall performance.

As described above, TE is the product of PTE and SE. DEA inefficiency is usually due to low PTE or SE, or both. Regarding the PTE of listed artificial intelligence companies, 7 companies have a PTE value of 1, accounting for 11.9% of the sample, with an average PTE value of 0.9084. This indicates that in actual operation, the artificial intelligence industry emphasizes the use of advanced management techniques and methods, significantly improving resource utilization, but there is still room for improvement. Regarding the SE of listed artificial intelligence companies, although only 5 companies have reached the efficient standard, the average SE is 0.9528, meaning that only 0.0472 of resources are not efficiently allocated, and the SE of most companies remains above 0.9. Therefore, relative to financial performance effectiveness, the main reason for the poor financial performance of listed artificial intelligence companies lies in the low PTE, indicating that the technical professionalism of the companies still needs to be further improved.

Overall, although the average values of these three efficiencies have not reached the efficient frontier, they are already in a relatively efficient state. This indicates that listed companies in the Chinese artificial intelligence industry are relatively efficiently utilizing resources at an appropriate scale, and are obtaining relatively higher financial performance returns.

4.2. Dynamic Efficiency Analysis of Listed Companies in the Artificial Intelligence Industry from 2018 to 2022

4.2.1 Chronological Analysis

Analyzing the operational efficiency of listed companies in the artificial intelligence industry dynamically is an important method to grasp their time series changes. In this process, combining the Malmquist index and DEA model constitutes an efficient analytical method. Therefore, based on data from 2018 to 2022, this study applied the Malmquist index for measurement. Table 3 below shows the annual operational efficiency indices of Chinese listed artificial intelligence companies during this period, along with their decomposition results.

Table 3 Malmquist Productivity Index and Decomposition of Listed Artificial Intelligence Companies by Year, 2018-2022

Time Period	Effch	Techch	Pech	Sech	Tfpch
2018-2019	1.009	0.976	0.97	1.04	0.984
2019-2020	1.046	1.247	1.016	1.029	1.305
2020-2021	0.991	0.962	1.007	0.985	0.953
2021-2022	0.942	1.081	0.966	0.976	1.015
Mean	0.997	1.067	0.99	1.009	1.064

From Table 2, it can be observed that Tfpch (Total factor productivity change) in the artificial intelligence industry over the five years is 1.064, implying an average annual growth rate of Tfpch of 6.4%. This indicates that the industry's development has seen relatively good utilization of various production factors, and overall, efficiency has shown an increasing trend. Specifically, Techch (Technical change) contributed to a growth of 6.7 percentage points, while Effch (Efficiency change) growth decreased by 0.3 percentage points, indicating a declining trend in the TE level of the artificial intelligence industry. At the same time, the growth of Tfpch in the artificial intelligence industry shows significant volatility, with a downward trend in 2018-2019 and 2020-2021, and an upward trend in 2019-2020 and 2021-2022.

From 2018 to 2019, the Malmquist index for Tfpch was 0.984, a decrease of 1.6%. The change in Effch was positive, while the change in Techch was negative, with an average annual decrease of 2.4%. This indicates that the decline in Tfpch in the artificial intelligence industry was mainly caused by the change in Techch, leading to an overall decrease in Tfpch.

From 2019 to 2020, the Malmquist index for Tfpch was 1.305, an increase of 30.5%. During this period, both the changes in Effch and Techch exceeded 1, with Techch contributing significantly to the substantial increase in total factor productivity.

From 2020 to 2021, the Malmquist index for Tfpch was 0.953, a decrease of 4.7%. During this period, both the changes in Effch and Techch contributed to this decrease, but Techch played a more significant role. In terms of Techch, Sech (Scale efficiency change) also decreased, with an average annual decrease of 1.5%, indicating that the scale of the artificial intelligence industry was not optimal in that year and needed to be further expanded. Overall, Tfpch decreased significantly.

From 2021 to 2022, the Malmquist index for Tfpch was 1.015, an increase of 1.5%, returning to an upward trend. The change in Techch was positive, with an average annual growth of 8.1%, indicating that the growth in Tfpch in the artificial intelligence industry was mainly driven by Techch. However, the improvement in Effch during the same period was relatively slow, with an average annual decrease of 5.8%, much lower than the 8.1% growth rate of Techch. This indicates that the development environment and prospects of the artificial intelligence industry are promising. During this period, there was a decrease in Effch and an increase in Techch, showing an overall upward trend. Techch contributed significantly to the improvement in Tfpch.

In summary, the financial performance of the artificial intelligence industry has shown a generally positive development trend, with the improvement in Techch being the main driving factor.

4.2.2 Regional analysis

During the "China´s "11th Five-Year" period, in order to coordinate regional development in China, it was necessary to establish a multi-level system and framework for regional division to implement targeted regional policies. At the first level, the country was divided into four main regions: the eastern, central, western, and northeastern regions, which cover the eastern, central, western, and northeastern regions of mainland China. The specific definitions of these four regions are as follows: the eastern region includes ten provinces and cities such as Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region includes eight provinces and regions such as Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan, Shaanxi, and Inner Mongolia (Shaanxi and Inner Mongolia, originally classified as western regions, are now included in the central region); the western region includes ten provinces, cities, and autonomous regions such as Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Gansu, Qinghai, Ningxia, Guangxi, and Xinjiang; the northeastern region includes three provinces such as Liaoning, Jilin, and Heilongjiang. Based on this classification, this study divides the selected 59 companies into eastern, central, western, and northeastern regions for analysis to explore regional differences in total factor productivity changes. The calculation results are shown in Table 4.

Table 4 Malmquist Productivity Index and Decomposition of Artificial Intelligence Listed Companies by Region, 2018-2022

Corporations(59)	Effch	Techch	Pech	Sech	Tfpch
Eastern region(50)	1.012	1.075	0.994	1.015	1.088
Central region(5)	1.006	1.045	0.999	1.001	1.054
Western region(3)	0.994	1.037	0.979	1.018	1.029
Northeastern region(1)	0.981	1.120	0.981	0.998	1.102

Among the 59 artificial intelligence companies, there are 50 in the eastern region, accounting for 85% of the total, 5 in the central region, 3 in the western region, and 1 in the northeastern region. It can be seen that artificial intelligence companies are mainly concentrated in the eastern region, including Beijing, Guangdong, Shanghai, Zhejiang, and Jiangsu, where there is a high concentration of AI talent, industrial parks for the transformation of research results, and a dense presence of venture capital institutions. This provides favorable conditions for the incubation of venture projects in Beijing, Shanghai, Guangdong, Jiangsu and Zhejiang. Due to the small sample size in the northeastern region, which lacks representativeness, this study did not conduct a detailed analysis of this region.

Among the 50 companies in the eastern region, the average dynamic change in Tfpch from 2018 to 2022 is 1.088, indicating an increase of 8.8% in Tfpch, which is higher than the overall improvement of 6.4% for all 59 companies. This further confirms that the productivity improvement in the eastern region is greater than the national average. Both changes in Effch and Techch have contributed to this growth, especially the change in Techch, which has increased by 7.5%.

Among the 5 companies in the central region, the average dynamic change in Tfpch from 2018 to 2022 is 1.054, indicating an increase of 5.4% in Tfpch, which is lower than the overall average of all 59 companies. This suggests that the improvement in productivity in the central region is relatively small, with the main contribution still coming from Techch, which has increased by 4.5%. Pech and Sech have increased by 0.1% and decreased by 0.1%, respectively.

Among the 3 companies in the western region, the average dynamic change in Tfpch from 2018 to 2022 is 1.029, indicating an increase of 2.9% in Tfpch. This is significantly lower than the overall average of all 59 companies. The main source of improvement is still Techch, which has increased by 3.7%, while Effch has decreased by 0.6%. Pech and Sech have decreased by 1.9% and 0.2%, respectively, negatively impacting the overall performance.

In conclusion, the most significant improvement in productivity is observed in the eastern region at 4.6%, followed by 2.8% in the western region and 2.2% in the central region. The primary source of Tfpch improvement in each region is the increase in Techch rather than the contribution from the increase in Effch (except in the eastern region), indicating a promising outlook for the development of the Chinese artificial intelligence industry. The Pech and Sech in each region are in a state of decline and rise, respectively. This suggests that the Chinese artificial intelligence industry has reached its optimal scale and can moderately and reasonably expand its scale. However, the management and technological levels of enterprises still need to be improved. How to transform the mode of economic growth and how to increase the intensity of efficiency improvement should be given more attention.

5. Conclusion

This study conducted a comprehensive analysis of the financial performance of Chinese artificial intelligence (AI) listed companies using the DEA-Malmquist model, exploring the operational efficiency of enterprises in the industry from both static and dynamic perspectives. Based on the static perspective analysis, it is known that the overall financial performance of Chinese listed AI companies is at a good level but has not yet reached its optimal state. The main challenge lies in the relatively low PTE, indicating the need for continued emphasis on technological innovation and efficiency improvement, especially in optimizing technology management and production processes. Based on the dynamic perspective analysis, it is found that the Tfpch of Chinese AI listed companies shows a fluctuating trend, but the overall development trend remains positive, with changes in most years approaching 1, indicating a continuous improvement in production efficiency. Particularly in the eastern region, where AI companies are highly concentrated, Sech has reached an optimal level, while Pech shows potential for further improvement. Overall, the financial performance of the Chinese AI industry presents a positive development trend. Techch has been confirmed as the main driving force, but it also reveals the potential for improvement in Effch. In addition, from a regional perspective, companies in different regions show different growth patterns and challenges, which require special attention.

Based on the above summary, this study makes the following recommendations:

Strengthen technological innovation and application. Technological advancement is the key to driving the development of the industry, and companies should increase their investment in the R&D and application of new technologies, especially in artificial intelligence and related fields. While focusing on technology R&D, it is also important to emphasize the market application of technology and business model innovation to ensure that the technology is transformed into actual economic benefits.

Improve technology efficiency. As pure technology benefits are low, the Company should focus on improving technology efficiency, which includes not only improvements at the technology level, but also optimization of management processes and operational efficiency. Efficient use of resources can be achieved by optimizing management and improving the level of technology application. This may include adopting advanced data analysis tools and improving production processes and resource allocation.

Focus on economies of scale. Enterprises should adjust the scale of production according to market demand and their own conditions. While maintaining flexibility, they should seek optimal economies of scale to improve overall financial performance. This means that enterprises should not only focus on the benefits brought about by expanding scale, but also consider the efficiency decline and cost increase that may result from over-expansion.

Coordination of regional development. Considering the uneven development of different regions, it is recommended that interregional coordination and cooperation be strengthened, especially in the sharing of technological resources and knowledge, to promote the overall development of the industry. Policymakers and industry leaders should consider policies that stimulate interregional cooperation, such as tax incentives and technology exchange platforms, to facilitate the flow of technology and knowledge.

By implementing these measures, the AI industry will not only be able to improve its financial performance, but also make a greater contribution to sustainable social and economic development.

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