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China's artificial intelligence efficiency and its influencing factors: Based on DEA-Malmquist and Tobit regression model

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C H R O N I C L E

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A B S T R A C T

The proliferation of artificial intelligence (AI) has emerged as a critical metric for assessing a country's technological advancement, but also for regional economic coordination and high-quality development in China. Based on panel data collected from 31 provinces between 2006 and 2021, this study employs the DEA-Malmquist index model and panel Tobit model to examine the scale, distributional attributes, and influencing factors of AI resource allocation. Results indicate that China's AI resource allocation efficiency has generally increased, with technical efficiency generating a "pull effect" that propels total factor productivity growth rates higher than those attributable to technological progress. Furthermore, AI efficiency in non-coastal regions outstrips that in coastal areas, with total factor productivity growth arising from a substantial increase in technological progress rates. Regional economic development, labor demand, openness to foreign participation, and human capital level exert pivotal roles in enhancing AI resource allocation efficiency. Based on these findings, we suggest a set of strategies aimed at enhancing China's AI resource allocation efficiency, including amplifying government guidance, increasing R&D investments, upgrading economic development levels, fostering the development and strengthening of tangible economy, and attracting and nurturing high-quality scientific research talent.

1. Introduction

Artificial Intelligence (AI) has emerged as a crucial driving force for the latest technological revolution and industrial transformation, with far-reaching implications for economic development, social progress, and international political and economic patterns (Zhang et al., 2023). The development and application of AI have been further clarified in the "Thirteenth Five-Year Plan for National Science and Technology Innovation" in 2016. The "New Generation AI Development Plan" was issued by the Chinese government in July 2017 and was explicitly proposed that AI should be closely meshing with the real economy, especially the manufacturing industry. A series of relevant documents were subsequently released to promote the evolution of AI. Along with policy planning, the release of national-level documents on AI talent cultivation, the construction of AI standard systems, and AI ethical norms has all played crucial roles in safeguarding the development of AI. This development indicates that AI has emerged as a significant strategic resource to drive economic growth and has flourished comprehensively in China. However, differences in resource allocation and integration efficiency among regions have led to significant disparities, and the region's economic development and innovation capacity are directly affected by these factors.

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2. Literature Review

In recent years, research on Chinese AI has become increasingly in-depth. With studies conducted on both the overall industry as well as its application in specific sectors. It is worth noting that there has been research on the trajectory of the Chinese AI industry's development, with Zhang et al. (2023) and Geng & Wang (2022) contributing to this area of inquiry. Moreover, research has explored the potential applications of AI in alleviating China's medical resource shortages and distribution inequalities(Kong et al., 2019). A further line of inquiry has prioritized the growth efficiency for the Chinese AI industry, principally by studying the data from listed companies in specific sectors, including manufacturing (Liu et al., 2019), intelligent automotive (You et al., 2018), robotics (Huang et al., 2017). Currently, research methods for assessing resource allocation efficiency can be broadly divided into parametric and non-parametric approaches. The parametric approach is primarily based on the Stochastic Frontier Approach (SFA), which requires high data model and raw data requirements, has limited model scalability (Xia & Li, 2023), and results in unstable efficiency estimates (Fiorentino et al., 2006). In contrast, Data Envelopment Analysis (DEA) is a significant non-parametric approach that is widely applied for assessing efficiency and productivity (Wanke et al., 2016). DEA explains more of the variability in both technical efficiency and economic efficiency than SFA (Heera & Kumar, 2023) and is more readily accepted than parametric methods (Svitalkova, 2014). In their research on technical efficiency using DEA, Nasierowski and Arcelus (2000) conducted a study on the efficiency of technological innovation in 45 countries and found a close association between the extent of technical innovation, the allocation of resources towards innovation. Subsequent studies by Huang et al. (2017) 、Hou and Zhu (2018) found that the R&D efficiency of Chinese AI companies is on the rise but still low, and has not reached DEA effectiveness. Decomposing the total factor productivity of AI, Liu and Hu (2020) found that the level of technical efficiency is a key determinant. However, Hou and Zhu (2018) and Ling and Hu (2020) found that technical progress can have a "drag effect," causing DEA to be ineffective in some companies, in addition to the main reasons of pure technical efficiency, there is also low scale efficiency (Liu et al., 2019). Furthermore, while analyzing the efficiency of AI, researchers also conducted heterogeneity analyses on different regions, predominantly according to the traditional East, Central, and West. They found that the regional heterogeneity effect of intelligence on development efficiency is significant, with the greatest effect in the east and the smallest in the west (Zhang & Xuan, 2022; Feng & Yu, 2020). Conversely, Qiu and Zhou (2021) and Li et al. (2020) argue that the promotion effect of intelligence on productivity is stronger in economically underdeveloped regions with low levels of innovation and a highly concentrated industry structure. Variations in resource endowments, management levels, and institutions among regions in China, while the development of AI will amplify these differences (Chen & Tang, 2021), it can also boost regional total factor productivity, narrow the economic quality gap (Hou & Song, 2021).

Despite scholars' abundant research results on AI resource allocation, the research perspectives have primarily focused on industries, enterprises, or individual provinces, cities, and city clusters, and few studies compare and evaluate different economic regions on a national scale. This study employs the DEA-Malmquist index model and panel Tobit model to examine the scale, distributional attributes, and influencing factors of AI resource allocation during 2006-2021. The objective is to contribute to enhancing technological innovation capabilities, optimizing AI resource allocation, and promoting high-quality regional economic development.

3. Methodology

3.1 DEA- ML Index

DEA was first introduced by Charnes and Cooper (1978) as a non-parametric linear programming approach for assessing the relative efficiency of decision-making units (DMU) in terms of their input and output indicators (Charnes et al., 1997). DEA offers four model selection options for evaluating input-output relative efficiency: input\output-oriented, and scale-constant\variable. The input-oriented model assesses DMU by minimizing inputs while keeping output constant, while the BCC model with variable returns to scale measures the pure technical and scale efficiency of research objects under the assumption of variable returns to scale. To measure the efficiency of regional AI resource allocation, we use an input-oriented BCC model due to significant differences in resource endowments and economic strength among regions. DEA models cannot provide reasonable calculations for dynamic efficiency (Zhang, 2020), so we use the Malmquist index (ML index) for this purpose. The ML index can analyze the dynamic changes in AI resource allocation efficiency across regions over time. It decomposes changes in total factor productivity (TFP) into comprehensive technical efficiency (EFFCH) and technological progress (TECH) components, with EFFCH further decomposed into pure technical efficiency (PECH) and scale efficiency (SECH). The input-oriented BCC model is used in this study to assess the efficiency of regional AI resource allocation due to the significant differences in resource endowments and economic strength among regions, and the uncertainty of both input and output of AI. The Malmquist index tracks modifications to the input-output EFFCH and TFP of DMU.

$$M(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)} \times \left[\frac{D^t(x_{t+1}, y_{t+1})}{D^{t+1}(x_{t+1}, y_{t+1})} \times \frac{D^t(x_t, y_t)}{D^{t+1}(x_t, y_t)}\right]^{\frac{1}{2}} \tag{1}$$

$$= \text{EFFCH} \times \text{TECH} \tag{2}$$

$$= (\text{PECH} \times \text{SECH}) \times \text{TECH} \tag{3}$$

In the Eq. (1), D^t and D^{t+1} denote the input-output relative efficiency of period t and period t+1. An efficiency improvement is indicated when M>1, while a stagnant state is represented by M=1. Efficiency decline is inferred when M<1.

3.2 Tobit Model

When measuring efficiency with the DEA model, these values are limited to 0 and 1.For dependent variables with limited values, the Tobit model is generally used for regression analysis based on maximum likelihood estimation (MLE)(Feng and Yu, 2020). The Tobit model is specifically formulated as follows:

$$y_i = \begin{cases} c_1 & \text{if} \quad y_i^* \le c_1 \\ x_i'\alpha + \varepsilon_i & \text{if} \quad c_1 \le y_i^* \le c_2 \\ c_2 & \text{if} \quad y_i^* \ge c_2 \end{cases} \tag{4}$$

In the Tobit model (4), α is the regression parameter vector, x_i is the explanatory variable vector, and the dependent variable is y_i. The typical form of the Tobit model sets c_1 0 and c_2 to positive infinity $+\infty$, ε_i is the random disturbance term follows N(0， σ^2).

4. Results and Discussion

4.1 DEA-ML index

This study defines the indicators by synthesizing prior research in order to guarantee the impartiality of the AI efficiency evaluation outcomes.When deciding on what to input indications, this study takes inspiration from the relevant indicators selection by scholars such as Chen and Tang (2021) and Zhang and Xuan (2022). The study also considers the principle of easy access to indicator data. Specifically, two output indicators, technology output and technology transfer, were selected, along with five input indicators, including human resources, financial resources, and infrastructure investment, in Table 1.

Table 1
AI resource input-output indicators

The Primary Indicators	Secondary Indicators	Tertiary Indicators	
INPUT	human resource	In1	Industrial enterprises above scale R&D personnel full time equivalent (person-years)
	financial resource	In2	Local financial expenditure on science and technology (billion yuan))
		In3	Fixed asset investment in the information transmission industry (billion yuan).
	infrastructure	In4	Internet broadband access ports (million)
		In5	Total length of long-distance fiber optic cables (million km)
OUTPUT	scientific and technological achievement output	Out1	Number of granted domestic patent applications (count).
	scientific and technological achievement conversion	Out2	Turnover in the technology market. (billion yuan)

To collect the necessary data for this study, we utilized panel data collected of 31 provinces between 2006-2021, with exception of Hong Kong, Macau, and Taiwan. These data sources were derived from several reputable publications including the “China Statistical Yearbook”, “China Science and Technology Statistical Yearbook”, and “China City Yearbook”. Table 2 displays the summary statistical findings for the selected indicators.

Table 2
Summary statistics

Variable	N	Mean	SD	Min	p25	p50	p75	Max
out1	497	96,839.86	1081118	68	4,734	17,093	50,488	24100000
out2	497	699.12	7,817.19	0	19.3	67.83	282.32	173,731.40
in1	497	222,231.20	2476035	635	27,122	62,304.60	135,829	55200000
in2	497	201.966	2,251.60	0.9	20.49	44.92	112.19	50,188.64
in3	497	309.861	3,450.55	0.6	52.91	100.5	207.68	77,000.45
in4	497	3,103.77	34,568.80	4.8	353.9	963.4	2,144.90	771,287.90
in5	497	5.933	66.026	0.08	2.15	3.02	3.8	1,474.43

4.1.1 Empirical Analysis of AI Total Factor Productivity

Adopting the input-oriented BCC model, this study assessed AI configuration effectiveness in 31 Chinese provinces via 2006, 2012, and 2021, using the DEAP2.1. Table 3 displays the static technical efficiency and breakdown items for the 31 provinces during a three-year period.

Table 3
The comprehensive efficiency for 2006, 2012 and 2021

DMU	2006				2012				2021			
	crste	vrste	scal	e	crste	vrste	scal	e	crste	vrste	scal	e
BJ	1	1	1	\	1	1	1	\	1	1	1	\
ZJ	1	1	1	\	1	1	1	\	1	1	1	\
CQ	0.957	1	0.957	+	0.7	1	0.7	+	1	1	1	\
FJ	0.682	0.711	0.959	+	0.603	0.732	0.824	+	1	1	1	\
SN	0.417	0.501	0.832	+	0.975	1	0.975	+	1	1	1	\
JX	0.389	0.548	0.71	+	0.361	0.614	0.588	+	0.99	0.994	0.996	+
TJ	0.944	1	0.944	+	0.661	1	0.661	+	0.973	1	0.973	+
QH	0.239	1	0.239	+	0.673	1	0.673	+	0.878	1	0.878	+
GD	1	1	1	\	0.626	0.626	0.999	\	0.872	1	0.872	-
JS	0.746	0.757	0.986	+	1	1	1	\	0.851	1	0.851	-
SH	1	1	1	\	1	1	1	\	0.833	1	0.833	+
SC	0.767	0.817	0.939	+	0.726	0.778	0.933	+	0.815	0.846	0.964	-
AH	0.4	0.523	0.766	+	0.64	0.683	0.937	+	0.747	0.748	0.999	+
SD	1	1	1	\	0.587	0.62	0.947	+	0.718	0.72	0.998	-
LN	0.612	0.649	0.944	+	0.516	0.552	0.935	+	0.692	0.915	0.756	+
GZ	0.413	0.51	0.81	+	0.617	0.9	0.686	+	0.688	0.726	0.948	+
XJ	0.599	0.651	0.92	+	0.328	0.513	0.639	+	0.669	0.733	0.912	+
HB	0.543	0.588	0.924	+	0.614	0.693	0.887	+	0.632	0.633	0.997	+
GS	0.355	0.551	0.644	+	0.481	0.799	0.602	+	0.617	0.723	0.853	+
HA	0.501	0.558	0.897	+	0.37	0.528	0.701	+	0.616	0.616	1	\
GX	0.263	0.373	0.703	+	0.211	0.328	0.643	+	0.593	0.613	0.967	+
HN	0.641	0.701	0.914	+	0.467	0.582	0.802	+	0.575	0.589	0.977	+
HL	0.461	0.493	0.935	+	0.63	0.721	0.873	+	0.553	0.563	0.982	+
HE	0.475	0.527	0.902	+	0.346	0.494	0.701	+	0.522	0.541	0.965	+
YN	0.369	0.404	0.914	+	0.402	0.493	0.815	+	0.477	0.499	0.956	+
NX	0.267	1	0.267	+	0.169	1	0.169	+	0.473	1	0.473	+
HI	0.712	1	0.712	+	0.238	1	0.238	+	0.394	1	0.394	+
JL	0.456	0.571	0.798	+	0.267	0.578	0.462	+	0.374	0.535	0.7	+
SX	0.263	0.409	0.643	+	0.256	0.477	0.537	+	0.368	0.565	0.65	+
XZ	0.281	1	0.281	+	0.164	1	0.164	+	0.346	1	0.346	+
NM	0.291	0.449	0.647	+	0.359	0.504	0.712	+	0.236	0.37	0.638	+
MEAN	0.582	0.719	0.812		0.548	0.749	0.736		0.694	0.804	0.867	

Table 3 presents that the efficiency of AI resource allocation in China follows a "V"-shaped trend, declining first and then increasing, and remains generally low. In each of the three years examined, only a few provinces achieved a comprehensive efficiency value of 1 for their AI resource allocation, indicating effectiveness in both PECH and SECH (vrste=1,scal=1), with the corresponding slack variables being 0. Specifically, in 2006 and 2021, the scale efficiency of 5 and 6 provinces, respectively, was higher than their pure technical efficiency. In 2012, PECH was higher than SECH(（0.749>0.736） in 11 provinces. The overall low EFFCH is mainly due to low SECH.

The level of PECH is an indicator of the management policies and level of regional AI resource allocation. The degree of growth in both the economy and society in every region is significantly associated with AI resource management. For instance, Beijing Zhejiang provinces are economically and technologically advanced, with relatively advanced AI technology and resource development, achieving DEA effectiveness in all three years. Shaanxi improved from 0.417 to 0.975 and achieved DEA effectiveness in 2021, while most other provinces showed a declining-first-then-rising trend consistent with the overall trend. Shaanxi, located in the northwest region, is home to many research institutions, universities, and a high-quality permanent population, making it a key region for AI resource allocation. Against the backdrop of "digitalization in the east and calculation in the west" and the western region's continuous development, AI resource allocation in Shaanxi is becoming more effective.

4.1.2 Trends in Efficiency of AI Resource Allocation

Dynamic analysis is more capable of reflecting changes in resource allocation efficiency than static analysis. From 2006 to 2021, the Malmquist index was used to quantify the dynamic changes in the productivity of AI resource allocation, Table 4 and Figure 1 illustrate the calculation results. The TFP of Chinese AI from 2006 to 2021, it grew by an average of 10% annually during the study period. This result is higher than the 8.2% of manufacturing calculated by Li et al. (2020), the

0.4% calculated by Ling and Hu (2020), and comparable to the 12.4% TFP of science and technology resources in the "Beijing-Tianjin-Hebei" calculated by Shu et al. (2021).

Table 4
The decomposition of TFP in 2006-2021

YEAR	EFFCH	TECH	PECH	SECH	TFP
2006-2007	1.10	0.91	1.06	1.04	1.00
2007-2008	0.97	1.02	0.99	0.98	**0.99**
2008-2009	0.91	1.21	0.96	0.96	1.10
2009-2010	0.99	1.20	1.01	0.98	1.19
2010-2011	0.96	1.13	1.02	0.94	1.09
2011-2012	1.00	1.13	1.02	0.98	1.13
2012-2013	1.05	0.99	0.96	1.09	1.04
2013-2014	1.09	0.90	1.07	1.03	**0.98**
2014-2015	1.17	1.08	1.06	1.11	1.26
2015-2016	1.00	0.99	1.00	1.01	1.00
2016-2017	1.17	0.90	1.12	1.05	1.05
2017-2018	1.12	1.16	1.04	1.08	1.30
2018-2019	0.99	1.00	1.00	0.99	**0.98**
2019-2020	1.02	1.34	1.00	1.03	1.37
2020-2021	1.01	1.16	1.01	1.01	1.18
mean	1.04	1.07	1.02	1.02	1.10

The TFP of AI resources shows a trend of fluctuating growth, except for the three periods of 2008-2007, 2014-2013, and 2019-2018, where the growth rate was less than 1. The growth rates in the other years were greater than 1, indicating an upward phase in the efficiency of AI resource allocation. EFFCH increased by 4% from 2006 to 2021, and TECH rate increased by 7%, with TECH contributing most to the growth of TFP, which is compatible with the findings of most experts, including Li (2019) and Ling (2020). SECH and PECH both rose at a 2% yearly pace, contributing to TFP growth. Fig. 1 shows that the overall trend of the changes in TFP and TECH from 2006 to 2021 is basically the same, indicating that TFP is mainly affected by TECH. The growth rate of China's AI resource PECH was stable from 2006 to 2021, with an average annual increase of 2%. The rise of EFFCH is primarily caused by the growth of SECH, which has a 2% yearly increase.

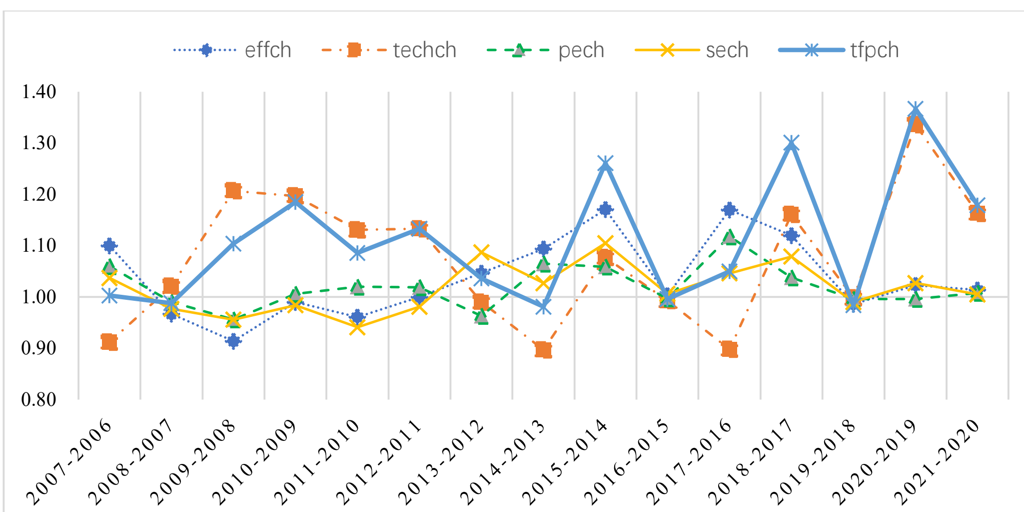

Fig. 1. Trends in the Malmquist Index of AI 2006-2021

From the perspective of time development, the efficiency of AI resource allocation can be divided into four stages before 2007, 2007-2013, 2013-2019, and after 2019. In the first and third stages, technical efficiency contributed mainly to the efficiency of allocation, while in the second and fourth stages, technical progress rate played a more important role. Overall, the TFP of China's AI resources is mainly affected by changes in technical progress, and the "pulling effect" of technical efficiency accelerates TFP growth faster than technical progress, and the overall trend is upward.

From a micro viewpoint, Table 5 investigates the dynamic shifts about productivity of regional AI resource distribution in China. In 2006-2021, the TFP showed an upward trend, and the AI resource allocation efficiency was greater than 1. Qinghai Province had the highest growth rate of 26%, while Hunan Province had the smallest growth rate of 1%. In terms of growth factors, the increase of TFP in Qinghai, Beijing, Tianjin, Liaoning, Shanghai, Shandong, Guangdong, Hainan, Sichuan, and other regions was mostly owing to TECH. In contrast, Fujian, Jiangxi, Guangxi, Ningxia, Tibet, and other regions had synergy between EFFCH and TECH. The low TFP in Hunan and Chongqing regions was mainly caused by PECH and SECH restrictions. Overall, TFP growth in China varied greatly, with the improvement owing to increased TECH.

Table 5
The ML Index and its decomposition of AI from 2006 to 2021

DMU	EFFCH	TECH	PECH	SECH	TFP	DMU	EFFCH	TECH	PECH	SECH	TFP
SH	1	1.08	1	1	1.08	LN	1.03	1.1	1.03	1	1.14
JS	1.02	1.06	1.02	1	1.09	JL	1.04	1.06	1.03	1	1.09
ZJ	1	1.06	1	1	1.06	HL	1.04	1.05	1.05	1	1.1
EC	1	1.07	1	1	1.07	**NE**	1.03	1.07	1.02	1.01	1.1
AH	1.04	1.05	1.02	1.02	1.09	BJ	1	1.05	1	1	1.05
JX	1.05	1.05	1.02	1.02	1.1	TJ	1	1.1	1	1	1.1
HB	1.03	1.05	1.02	1.01	1.08	HE	1.05	1.03	1.04	1.01	1.09
HN	0.98	1.03	0.98	1.01	1.01	SD	1	1.08	1	1	1.08
MC	1.01	1.06	0.99	1.02	1.06	**NC**	1	1.057	1	1	1.06
SX	1.06	1.08	1.03	1.03	1.14	FJ	1.03	1.03	1.02	1	1.06
NM	1.08	1.07	1.05	1.03	1.16	GD	1	1.08	1	1	1.08
HA	1.02	1.05	1.02	1.01	1.08	HI	1.02	1.08	1	1.02	1.11
SN	1.06	1.07	1.05	1.01	1.13	**SC**	1	1.075	1	1	1.08
MY	1.04	1.04	1.02	1.03	1.09	GX	1.09	1.08	1.07	1.02	1.18
XZ	1.09	1.09	1	1.09	1.19	CQ	0.99	1.03	1	0.99	1.02
GS	1.06	1.05	1.03	1.02	1.11	SC	1	1.06	1	1	1.05
QH	1.1	1.14	1	1.1	1.26	GZ	1.05	1.07	1.04	1.01	1.13
NX	1.08	1.08	1	1.08	1.17	YN	1.05	1.09	1.04	1	1.14
XJ	1.04	1.09	1.03	1.01	1.13	**SW**	1.02	1.05	1	1.02	1.08
NW	1.04	1.12	1	1.04	1.16	**Mean**	1.04	1.07	1.02	1.02	1.1

4.1.3 Regional analysis

The present study conducts a regional analysis of China's AI resources' TFP, using the eight comprehensive economic regions. The findings of the analysis from 2006-2021 reveal an overall upward trend in the configuration efficiency of AI resource allocation in these zones, as demonstrated in Fig. 2 and Fig. 3. Nevertheless, there remain considerable differences in efficiency levels between regions, with some regions failing to achieve DEA effectiveness. The East coast displays the most substantial variation in AI resource configuration, with an apparent “V” shape, and efficiency levels reaching their lowest point in 2013-2014. This can be attributed to low TECH and SECH. In contrast, the Middle Yellow River has achieved effective DEA status since 2009, owing to the simultaneous increase of PECH and SECH.

The study's findings indicate that the AI TFP of all eight economic zones from 2006-2021 exceeded one, with all regions displaying DEA effectiveness (Figure 3). The regions' ranking, based on their AI TFP levels from high to low: Northwest (1.164), Northeast (1.099), Middle Yellow River (1.088), Southwest (1.076), Southern Coastal (1.075), Eastern Coastal (1.074), Middle Yangtze River (1.063), and Northern Coastal (1.057). The findings also indicate an overall upward trend in all the zones, with an average growth rate of 8.7%. Only the Middle Yangtze River displayed PECH inefficiency, whereas all other regions had effective TECH and EFFCH.

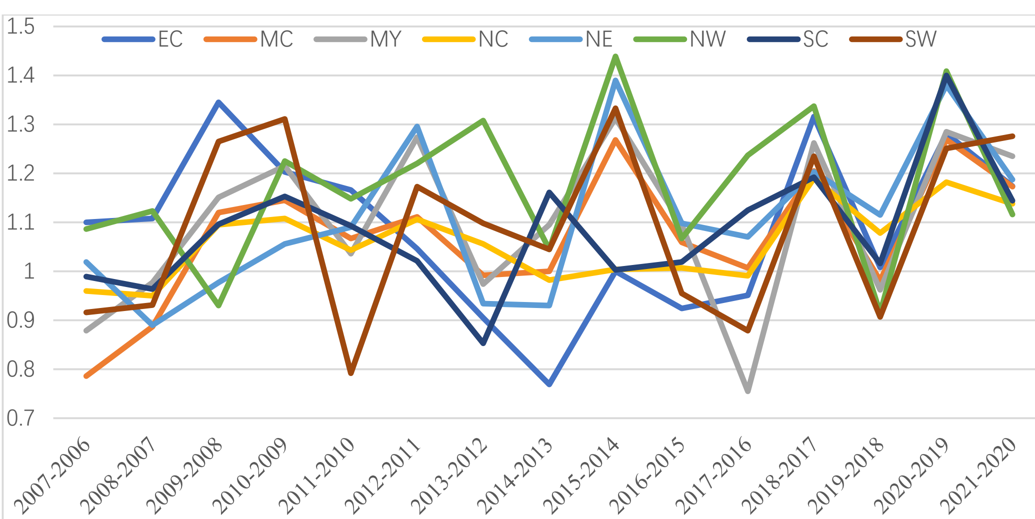

Fig. 2. Trends in theTFP of AI in the eight economic regions, 2006-2021

The Northwest, Northeast, and Middle Yellow River generally exhibit a higher development level than the national average, owing to the rapid growth of scale efficiency, which agrees with the findings of Qiu Zixun, et al. (2020) and Li Lianshui, et al. (2019). For example, the TFP of the Middle Yellow River rose from 0.879 to 1.235 between 2006 and 2021, an increase of 35.6%. Conversely, the Northern Coastal displayed the lowest TFP, followed by the Middle Yangtze River, Eastern Coastal, and Southern Coastal. This is likely due to the eastern and coastal regions having a more developed AI industry and a better foundation for TFP. As a result, their productivity development has limited room for improvement and shows a slow upward trend. However, the central, western, and northern regions lag in AI application in industries, with weak productivity levels. In recent years, national policies have supported the development of AI, resulting in a rapid improvement in productivity. Nonetheless, the results of Cui Qi's 2022 green TFP calculation indicate the opposite, possibly due to the non-consideration of unexpected output.

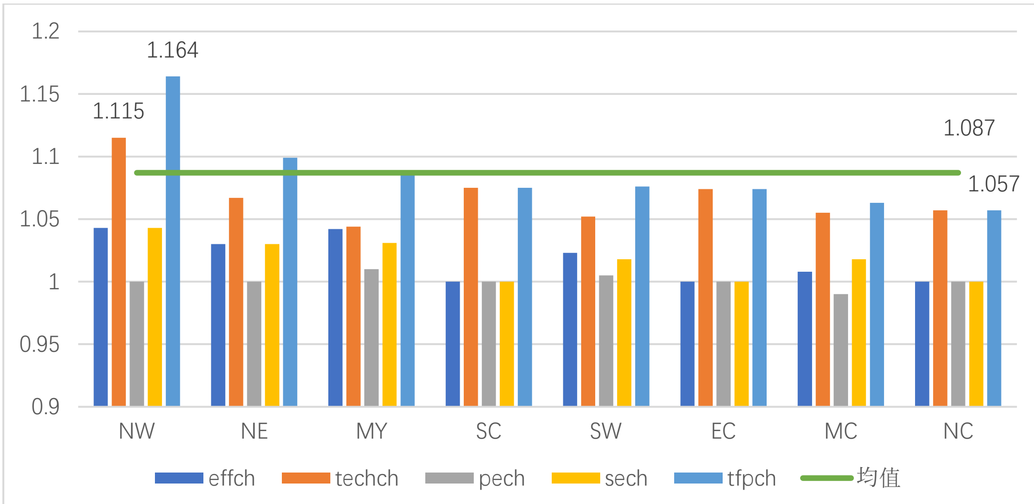

Fig. 3. AI Malmquist Index and its decomposition of China, 2006-2021

The TFP of the eight economic regions in China demonstrated an upward trend, supported by both technological progress and efficiency. However, the predominant driver was the improvement in technological progress, particularly in the northern regions where progress was significantly faster than in the south. The Northwest, Northeast, and the Middle Yellow River of China exhibited relatively high levels of AI TFP ranking, largely due to the rapid improvement of technology progress. In addition, the Middle Yellow River demonstrated improved technological efficiency. The Northern coastal and the Middle Yangtze River should concentrate on improving their developmental efforts, adapting to the requirements of new technologies, and improving technological efficiency to narrow the gap with the optimal output. Meanwhile, the eastern and southern coastal areas did not exhibit prominent advantages, particularly in the case of the former, where low-level intelligence cannot significantly promote TFP. Enhancing technological progress efficiency requires a concentrated effort on breaking through the constraints of core technologies in addition to strengthening management to improve technological efficiency.

4.2 Factors Affecting the Efficiency of Resource Allocation in AI

It investigates major impacting elements of China's AI resource allocation efficiency by selecting five variables: economic development level, human capital level, labor demand, degree of openness, and industrial structure upgrading. Economic development level (GDP) is measured by the domestic real gross domestic product, which is adjusted for inflation based on 2006 as the base period. The overall number of employed persons in society is used to calculate labor demand (JOB). The degree of openness (DUF) is represented by the total import and export volume, translated into RMB using the current year's average US dollar-to-RMB exchange rate and adjusted for inflation based on 2006 as the base period. Human capital level (HR) is measured by the number of higher education students per 100,000 population. The degree of industrial structure upgrading (STRU) is calculated using the method of Xu (2008)[1], the closer to 3, the higher industrial structure upgrading and the closer to the information economy society (or knowledge economy society). Higher levels of GDP, JOB, DUF, HR, and STR Review of the literature U are positively correlated with higher efficiency of AI resource allocation. The TOBIT regression equation is constructed as in equation (5):

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[1] Calculation method: STRU = percentage of GDP from the primary sector * 1 + percentage of GDP from the second sector * 2 + percentage of GDP from the third sector * 3. The more advanced the degree of improvements to the industrial structure and the higher the economic level, the closer it is to the information economy society (or knowledge-based economy society).

$$TFP_{it} = c + \alpha_1 \ln(GDP_{it}) + \alpha_2 \ln(JOB_{it}) + \alpha_3 \ln(DUF_{it}) + \alpha_4 \ln(HR_{it}) + \alpha_5 STRU_{it} + \varepsilon_{it} \quad (5)$$

A Tobit regression model is utilized in the current research to analyze the factors that impact the effectiveness of resource allocation for AI in China. The model (5) includes i, representing the 31 provinces in China, and t, representing the year. To reduce multicollinearity, a logarithmic transformation is applied to the absolute quantity indicators. The coefficients of the model are estimated based on the partial effects of y, as the coefficients themselves lack direct interpretations (Cameron & Trivedi, 2005). The impact of independent variables on TFP is shown in the first column of Table 6. The results indicate that JOB, DUF, and HR possess a detrimental impact on the efficiency with which AI resources are allocated, while GDP contributes to the improvement of such efficiency， the impact of the STRU is not significant.

Table 5 further demonstrates that the EFFCH of the three coastal zones (NC, EC, and SC) is 1, indicating that they have just reached DEA effectiveness, and their TFP values are lower than those of other regions. Subsequently, the study divides the 31 provinces into coastal (10 provinces) and non-coastal (21 provinces) areas and conducts a Tobit regression analysis on subsamples. Table 6 reveals that the effect of economic development level, labor demand, openness, human capital, and industrial structure are greater for non-coastal areas and the significance remains consistent with the overall, and is not significant for coastal areas. In contrast, the effects on coastal areas are not significant.

Table 6
Tobit regression results

	(1) TFP	(2) non-coastal	(3) coastal
lnGDP	0.134***	0.124*	0.0753
	(2.64)	(1.83)	(0.79)
lnJOB	-0.136***	-0.162***	-0.00796
	(-2.82)	(-2.70)	(-0.09)
lnDUF	-0.0369**	-0.00369	-0.0526
	(-2.22)	(-0.11)	(-1.45)
lnHRC	-0.133**	-0.163*	0.0748
	(-2.30)	(-1.93)	(0.61)
STRU	0.0725	0.214	-0.0327
	(0.43)	(0.76)	(-0.11)
_cons	2.057***	2.022**	0.405
	(3.90)	(2.47)	(0.47)
N	465	315	150

z statistics in parentheses， * p<0.1, ** p<0.05, *** p<0.01

The impact of China's economic development, labor demand, human capital, industrial structure, and openness to the outside world on the effectiveness of AI resource allocation. According to the findings in Table 5, the effectiveness of AI resource allocation is positively associated with the degree of economic growth, as increased scientific and technological investment, design, production, and other aspects of AI leads to higher efficiency of resource allocation. However, this conclusion also applies to non-coastal areas, the level of economic development is generally lower in non-coastal areas, resulting in lower investment intensity in research and development and lower efficiency of resource allocation. From 2007 to 2021, the local financial expenditure on science and technology in coastal areas was 65.7 billion yuan, while that in non-coastal areas was 23.3 billion yuan. When funding is insufficient to support research and development activities, it is easy to suppress technological innovation, affecting the efficiency of resource allocation.

Another finding of the study indicates that the efficiency of resource allocation for AI decreases as the demand for labor across society increases. As AI technology has a substitution effect on labor, The more advanced the degree of AI technology, the larger the labor substitution impact, resulting in less demand for labor. Non-coastal areas are mainly dominated by the primary and secondary industries and have a large number of low-skilled laborers, leading to relatively low labor costs that undermine incentives for corporate R&D and technological innovation, resulting in lower efficiency of resource allocation. Similarly, strong labor demand can push up labor costs and crowd out funds for R&D and innovation.

Furthermore, the study finds a negative correlation between openness and AI resource allocation efficiency. Although the fact that openness may facilitate technology exchange and cooperation, it may also attract competitors with larger scales, more advanced technology, and stronger capabilities. This competition is not only detrimental to the development of primary AI technology in its infancy, but may also lead to the repetition and waste of work, the waste of resources, and the decline in efficiency, ultimately affecting the efficiency of AI resource allocation.

5. Conclusion

The DEA - ML model is used in this article to assess China's AI resource allocation effectiveness in 2006 - 2021. The findings show that:

First, China's overall AI resource allocation efficiency experienced an increasing fluctuation pattern throughout the research interval, with some variations among provinces, but generally with high efficiency. The study found that TFP of AI in all 31 provinces achieved DEA effectiveness throughout the research era, and the "pull effect" which EFFCH led to a growth rate of TFP higher than that of technological progress.

Second, from 2006 to 2021, the TFP of AI in the eight comprehensive economic regions was greater than 1 and DEA-effective. However, the economically developed areas such as the Coastal areas had relatively low values of AI resource allocation efficiency.

Third, China's artificial intelligence is now undergoing fast development. The economic development and artificial intelligence technology foundation in non-coastal areas are relatively weak, but with the fast expansion of the social economy in the past few years, labor resources and human capital have been rationally distributed with artificial intelligence resources, achieving DEA effectiveness. The level of artificial intelligence in coastal areas is relatively high, but it is still at a low level and difficult to match the highly developed economic situation, and the allocation efficiency of artificial intelligence resources is low. Therefore, this article suggests that the government should take an active role in classification guidance, update low-level intelligent technologies, and increase research and development investment in AI to break through core technologies, achieve high-level development of AI, and further improve TFP. T In the center and western areas, the emphasis ought to concentrate on developing the integration of AI and the actual economy. applying intelligent technologies in design, production, management, and other links, improving the popularity and utilization rate of enterprise intelligence. The government should encourage cooperation and communication among regions, promote innovation and reform, attach importance to the training of scientific research talents, speed the transition of advances in science and technology accomplishments, and strengthen managerial ability in order promote both the driving forces of TECH and EFFCH. By doing so, the TFP of AI can be improved, and the stable growth of regional AI efficiency can be ensured.

Finally, each region should increase research and development investment, promote further improvement of the intelligence level, and amplify the promoting effect of AI on TFP, while improving resource allocation capabilities to avoid unnecessary waste.

References

Cameron, A., & Trivedi, P. (2005). Microeconometrics: Methods and Applications. https://doi.org/10.1017/CBO9780511811241

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Charnes, A., Cooper, W., Lewin, A. Y., & Seiford, L. M. (1997). Data Envelopment Analysis Theory, Methodology and Applications. *Journal of the Operational Research Society, 48*(3), 332–333. https://doi.org/10.1057/palgrave.jors.2600342

Chen, D. Y., & Tang, Y. G. (2021). Impact of Artificial Intelligence Industry on Regional Economic Development. *Science and Technology Management Research, 41*(2), 138–144.

Cui, Q., Ma, X. Y., & Zhang, S. S. (2022). Study on Evaluation and Influencing Factors of Green Total Factor Energy Efficiency Analysis : Based on Data from China's Eight Economic Regions. *Journal of Technical Economics & Management, 3*, 94–99.

Feng, R., & Yu, X. (2020). TFEE Measurement, Decompositionand Influencing Factors Analysis of EightEconomic Regions in China. *Polish Journal of Environmental Studies, 29*(6), 4291–4301. https://doi.org/10.15244/pjoes/120086.

Fiorentino, E., Karmann, A., & Koetter, M. (2006). The cost efficiency of German banks: A comparison of SFA and DEA. Banking and Financial Studies.

Geng, Z. H., & Wang, W. X. (2022). Research on Development Trend and lnfluencing Factors of China's Artificial Intelligence Industry. *Enterprise Economy, 41*(3), 36–46. https://doi.org/10.13529/j.cnki.enterprise.economy.2022.03.004

Heera, S. N., & Kumar, K. N. R. (2023). Economic analysis of groundnut farmers participating in Rythu Bharosa Kendras (RBKs) in Guntur district of Andhra Pradesh. *The Pharma Innovation, 12*(3), 5586–5590.

Hou, S. Y., & Song, L. R. (2021). The Impact of Intelligentization on the Quality of Ｒegional Economic Growth and Its Internal Mechanism: Based on 2012 － 2018 Provincial Panel Data in China. *Journal of Guangdong University of Finance and Economics, 36*(4), 4–16.

Hou, Z. J., & Zhu, C. L. (2018). China's Artificial Intelligence Enterprise Total Factor Productivity and Its Influencing Factors. *Enterprise Economy, 37*(11), 55–62.

Huang, J., Yang, Z., Yin, L., Zhang, M., & Qin, Y. (2017). Analysis on R&D Efficiency of Domestic Robot Enterprises and Related Factors in China Based on DEA-Tobit Two-Stage Analysis Method. *Science & Technology Progress and Policy, 34*(18), 101–106.

Kong, X., Ai, B., Kong, Y., Su, L., Ning, Y., Howard, N., Gong, S., Li, C., Wang, J., Lee, W.-T., Wang, J., Kong, Y., Wang, J., & Fang, Y. (2019). Artificial intelligence: A key to relieve China's insufficient and unequally-distributed medical resources. *American Journal of Translational Research, 11*(5), 2632–2640.

Li, L., Bao, Y., & Liu, J. (2020). Research on the influence of intelligentization on total factor productivity of China's manufacturing industry. *Studies in Science of Science, 38*(4), 609-618+722. https://doi.org/10.16192/j.cnki.1003-2053.2020.04.006

Ling, F., & Hu, D. (2020). Efficiency of Technology lnnovation in China's Artificial lntelligence lndustry: Based on DEAand Malmquist Index. *Journal of Hubei University of Arts and Science, 41*(8), 47–52.

Liu, C., Fu, R., Li, J., & Zhou, W. (2019). Research into Financing Efficiency of Artificial Intelligence Industry Based on DEA-Tobit Method. *Operations Research And Management Science, 28*(6), 144–152.

Liu, L., & Hu, G. (2020). Artificial Intelligence and Total Factor Productivity: Chinese Proof of "Productivity Dilemma' Falsification. *Jianghai Academic Journal, 3,* 118–123.

Nasierowski, W., & Arcelus, F. J. (2000). On the stability of countries' national technological systems (pp. 97-111). Springer US.

Qiu, Z., & Zhou, Y. (2021). Development of Digital Economy and Regional Total Factor Productivity: An Analysis Basedon National Big Data Comprehensive Pilot Zone. *Journal of Finance and Economics, 47*(7), 4–17.

Shu, T., Nie, X., Guo, H., Li, X., & Bai, B. (2021). Analysis on the Efficiency of Scientific and Technological Resource Allocation in Beijing-Tianjin-Hebei Urban Agglomeration: Based on DEA-Malmquist Index Model. *Science and Technology Management Research, 41*(4), 89–96.

Svitalkova, Z. (2014). Comparison and Evaluation of Bank Efficiency in Selected Countries in EU. *Procedia Economics and Finance, 12,* 644–653. https://doi.org/10.1016/S2212-5671(14)00389-X

Wanke, P., Azad, M. D. A. K., & Barros, C. P. (2016). Predicting efficiency in Malaysian Islamic banks: A two-stage TOPSIS and neural networks approach. *Research in International Business and Finance, 36*, 485–498. https://doi.org/10.1016/j.ribaf.2015.10.002

Xia, M., & Li, X. (2023). Research on technology innovation efficiency and influencing factors in Beijing-Tianjin-Hebei, Yangtze River Delta, West River Delta and Pearl River Delta —— Empirical analysis based on DEA-Malmquist and multiple regression model. *Journal of Liaoning University of Technology(Social Science Edition), 25*(2), 12-18+35.

Xu, D. (2008). An Theoretical Explanation and Validation of the Determination and Measurement of the Form of Industrial Structure Upgrading. *Fiscal Research, 1,* 46-49.

You, J., Xu, T., & Yu, A. (2018). Process for Companies in Intellectual Vehicle Industry Evaluation of Operational Efficiency with the Consideration of Corresponding innovation. *Journal of Tongji University(Natural Science), 46*(1), 133–140.

Zhang, C. (2020). Total Factor Productivity Analysis of Regional Differences in Economic Development in China —— Based on DEA Model of Malmquist Index Perspective. *Journal of Technical Economics & Management, 9*, 118–122.

Zhang, C., Xu, Y., & He, X. (2023). Research on the Development Path of China's Artificial Intelligence Industry -- Based on the Comparison of Chinese and American Artificial Intelligence. *Studies in Science of Science,* 1–19. https://doi.org/10.16192/j.cnki.1003-2053.20230221.001

Zhang, W., & Xuan, Y. (2022). How to Improve the Regional Energy Efficiency via Intelligence? Empirical Analysis Based on Provincial Panel Data in China. *Business and Management Journal, 44*(1), 27–46.