Does artificial intelligence have the potential to improve total factor energy efficiency? — Empirical evidence from 30 Chinese provinces

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Abstract. As the level of AI technology improves, AI technology plays an important role in responding to energy. The article empirically investigates the impact of AI technology on total factor energy efficiency(TFEE) in China using provincial panel data from 2010 to 2019. The finding shows that artificial intelligence technology has a significant positive impact on total factor energy efficiency. As a result, China should accelerate the development and promotion of AI policies in the energy sector, strengthen AI talent training, and expand the use of AI in energy policy formulation to promote the development of the energy industry toward greater intelligence, efficiency, and sustainability.

Keywords: Artificial Intelligence, Total Factor Energy Efficiency, Empirical Analysis.

1 Introduction

Artificial intelligence technologies have been widely used in the energy sector in recent years to improve energy efficiency and reduce energy consumption. Artificial intelligence is a potent technological tool that has been applied in a variety of industries.For example, smart energy management systems, rely on AI technology to automate the process of managing energy consumption and improving energy efficiency.The application of artificial intelligence technology in the energy field will promote the evolution of the energy industry toward greater intelligence, efficiency, and sustainability, and will contribute positively to the realization of energy transformation and sustainable development [1][2].

According to a study of the impact of AI on total factor energy efficiency, AI has a positive contribution to energy efficiency [3]. Scholars have further investigated the mechanisms and impact channels of AI on energy efficiency on this basis. Zhang S, et al (2021) [4] demonstrated that with the continuous advancement of AI technology level, the digital economy can significantly contribute to TFEE by increasing economic growth level, urbanization level, R&D investment, and human capital. Merabet, et al (2021) [5] investigated artificial intelligence (AI) technology for building energy management systems (BEMS) conducted a thorough review and

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concluded that these technologies can improve energy efficiency while taking thermal comfort into account. Li J,et al (2022) [6] created a digital economy index and a green economy efficiency index based on panel data from 277 Chinese cities from 2011 to 2018, demonstrating that the digital economy can significantly improve green economy efficiency in the context of AI technology development. Liu J, et al (2022) [7] investigated the impact of AI on the energy efficiency of manufacturing enterprises using comprehensive survey data from enterprises above the scale in Guangdong Province. The findings show that AI can help manufacturers improve their energy efficiency.

To summarize, existing research on AI and total factor energy efficiency provides a theoretical foundation for our future research, but there is still much work to be done. In this paper, we show how AI technology advancements can contribute to total factor energy efficiency, providing a new perspective for future policy design.

2 Theoretical analysis and research hypothesis

The extensive use of internet digital technologies has accelerated industrial integration and changed the industrial structure, affecting regional total factor energy efficiency [8]. Artificial intelligence technologies can also help traditional industries digitally transform by improving the efficiency of production, transmission, storage, and distribution. It also incorporates energy-efficient technologies into products, which leads to an increase in total factor energy efficiency [9]. As an emerging resource allocation tool in the market economy, the internet can reconfigure labor, capital, and other factors to promote the industrial structure to the upper reaches of the industrial chain, thereby improving total factor energy efficiency [10].In summary of the above analysis, this paper proposes the the following hypothesis.

The advancement of artificial intelligence technology has a significant impact on promoting total factor energy efficiency improvement.

3 Description of the empirical econometric model and data

3.1 Model setting

To begin, the following benchmark regression model is constructed in this paper to test the impact of AI technology development level on total factor energy efficiency.

$$\mathrm{TFEE}_{it} = \alpha_0 + \alpha_1 \mathrm{AI}_{it} + \alpha_2 \mathrm{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

In the model, TFEE_{it} denotes the degree of population aging in region i in period t, AI_{it} denotes the level of AI technology development in region i in period t, X_{it} denotes the relevant control variables; α_0 denotes the intercept term, α_1 and α_2 denote the parameter estimates of AI technology development and control variables on total factor energy efficiency, respectively; μ_i denotes the provincial fixed effect, λ_t denotes the time fixed effect, and ε_{it} is the random disturbance term. Therefore, the model mainly discusses the effect of AI on total factor energy efficiency. Therefore, the main focus is on the magnitude of the α_1 value.

3.2 Variable selection and data description

Explanatory Variables

Total factor energy efficiency is the explanatory variable in this paper (TFEE). Input indicators for total factor energy efficiency (TFEE) primarily include capital stock, labor input, and energy consumption. Output indicators include both desirable and non-desirable output. According to previous research, GDP is chosen as a measure of desirable output, and SO2 emissions from energy inputs are chosen as a measure of non-desirable output.

(1)Capital stock (K): Capital stock is used as an indicator of capital in this paper. The capital stock is calculated using the perpetual inventory method and the formula below.

$$K_t = K_{t-1}(1 - \delta_t) + I_t \tag{2}$$

where K_t denotes the current capital stock, K_{t-1} denotes the prior period capital stock, δ_t denotes the depreciation rate, and I_t denotes the current depreciation amount. To exclude the effect of price changes, the capital stock was estimated using 2010 constant prices. The formula for the base period capital stock is as follows.

$$K_0 = I_1/(g_i + \delta) \tag{3}$$

Where K_0 represents the capital stock of each province in 2010, I_1 represents the investment amount in 2011, g_i represents the average growth rate of the investment amount from 2011 to 2019, and δ represents the depreciation rate. The depreciation rate is uniformly set at 10.96%. The data required for the calculations were obtained from the China Statistical Yearbook.

(2)Labor input (L): from 2010 to 2019, the labor input data is the number of employed people at the end of the year in each province, with the unit being million.

(3)Energy consumption (R): The energy input data in this paper represent the total energy consumption of each province in million tons.

(4)Expected output (Y): The GDP of each province is chosen from 2010 to 2019, and the unit is billion.

(5)Non-desired output (E): Selected SO2 emissions per province in million tons from 2010 to 2019.

The following equation is used to calculate total factor energy efficiency using the Slack-based measurement data envelope analysis (SBM-DEA) model.

$$\rho^* = \min \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_1}{x_{i0}}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^{g}}{y_{r0}^{g}}+\sum_{r=1}^{s_2}\frac{s_r^{b}}{y_{r0}^{b}}\right)} \tag{4}$$

s.t.

$$\begin{cases} x_0 = X\lambda + s^-, \\ y_0^g = Y^g\lambda - s^g \\ y_0^b = Y^b\lambda + s^b \\ s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0 \end{cases}$$

Core explanatory variables

The level of artificial intelligence is the primary explanatory variable in this paper (AI). The installation density of robots in each province (units/1000 people) is chosen in this paper to reflect the actual application level of AI.

Control variables

The control variables chosen for this paper primarily include.

(1) Regional government intervention level (GOV): In each region, the ratio of general government spending to regional GDP.

(2) Population size (PS): The total population of each province is expressed in millions of people.

(3) Science and technology activities (RD): Each province's choice of RD science and technology research and development investment is expressed in million yuan.

(4) Industrial structure (AIS): The expression for the quality of high polarization of industrial structure is as follows.

$$ais_{it} = {}_{m=1}^{3} y_{i,m,t} \times lp_{i,m,t}, m = 1,2,3 \tag{5}$$

where $lp_{i,m,t}$ is the level of real labor productivity in industry m in region i at time t, as expressed by the following equation.

$$lp_{i,m,t} = Y_{i,m,t}/L_{i,m,t} \tag{6}$$

where $Y_{i,m,t}$ and $L_{i,m,t}$ denote the value added and the number of employed persons in industry m on region i in period t, respectively.

(5) Service Industry Level (SIL): This indicator is based on the total number of people employed in China's service industry, expressed in thousands.

3.3 Data sources

The data in this paper are from previous years' China Statistical Yearbook, World Robotics Report, and National Statistical Bulletin of Science and Technology Funding Inputs. Table 1 displays the descriptive statistics for the main variables in this paper.

Table 1. Descriptive statistics of variables

Variable	Obs	Mean	Std. Dev.	Min	Max
TFEE	300	0.177	0.155	0.054	1
AI	300	0.300	0.237	0.036	1.29
GOV	300	0.260	0.115	0.024	0.758

SIL	300	2859.904	1695.921	331.289	10642.57
RD	300	0.003	0.005	0.0003	0.029
PS	300	4.575	2.809	0.563	12.489
AIS	296	1.1164	0.575	0.454	5.553

4 Empirical Results and Analysis

4.1 Baseline regression

To test whether AI can effectively promote total factor energy efficiency, this paper employs a time-provincial two-way stationary model.Column 1 of Table 2 excludes control variables as well as fixed effects; column 2 considers only province fixed effects; column 3 considers both province and time fixed effects; columns 4–6 include control variables, and the other conditions are the same as in columns 1–3.

The regression results of models (1) to (6) in Table 2 show that the AI coefficients are all significantly positive at the 1% level, and AI has a significant contribution to total factor energy efficiency, which verifies the hypothesis of this paper.

Table 2. Baseline regression results

	(1) TFEE	(2) TFEE	(3) TFEE	(4) TFEE	(5) TFEE	(6) TFEE
AI	0.291^{***}	0.291^{***}	0.252^{***}	0.220^{***}	0.218^{***}	0.214^{***}
	(12.54)	(12.42)	(4.34)	(8.34)	(7.16)	(3.87)
_cons	0.089^{***}	0.089^{***}	0.077^{***}	0.120^{***}	0.552^{***}	0.625^{***}
	(3.95)	(10.50)	(4.95)	(2.93)	(2.96)	(3.36)
Control variables	N	N	N	Y	Y	Y
provincial fixed effects	N	Y	Y	N	Y	Y
Time fixed effects	N	N	Y	N	N	Y
Sample size	300	300	300	296	296	296

Note: *, **, *** indicate that the estimated coefficients are significant at the levels of 0.1, 0.05, and 0.01, respectively, and the t-statistics are in parentheses.

4.2 Endogeneity treatment

This paper attempts to address potential endogeneity issues caused by omitted variables, two-way causality, and measurement errors using IV-2SLS(Instrumental variables estimation using Two-Stage Least-Squares) method. As an instrumental variable, a new variable iAI is constructed. iAI is the lagged one period of AI.

Table 3. Endogeneity test

	（1） TFEE	（2） TFEE
AI	0.278***	0.274***
	（0.0662）	（0.0673）
_cons	0.494***	0.499***
	（0.0489）	（0.0495）
	First stage of return	
iAI	0.903***	0.879***
	（0.0312）	（0.0326）
Control variables	N	Y
Wald test	(Size of nominal 5% 16.38)	(Size of nominal 5% 29.18)
Hansen-J statistic	0.575	9.270
(p-value)	(0.4484)	(0.1590)
provincial fixed effects	Y	Y
Time fixed effects	Y	Y
Sample size	270	266

Note: *, **, *** indicate that the estimated coefficients are significant at the levels of 0.1, 0.05, and 0.01, respectively, and robust standard errors are in parentheses.

The hypothesis of this paper are all valid after accounting for endogeneity. Table 3 Under the conditions of controlling control variables and uncontrolled variables, models (1) and (2) were tested for endogeneity using time-provincial two-way stationary models.The test results showed that the coefficient of iAI was significantly positive at the 1% level, indicating that the level of AI is positively proportional to the lagged term of AI level, and the lagged term of AI level is inversely proportional to total factor energy efficiency, and the hypothesis of this paper is valid. Furthermore, both models in Table 3 pass the weak instrumental variable identification test, indicating that the instrumental variables chosen in this paper are reasonable.

4.3 Robustness test

The following dynamic panel model is used to investigate the effect of AI on energy intensity, which is the amount of energy consumed per unit of output value and is generally measured in tons of standard coal (or tons of standard oil, etc.) per 10,000 yuan of gross domestic product (GDP). The lower the energy intensity, the more efficient and effective the production and energy use. Table 4 shows that increasing the AI level can effectively reduce energy intensity, and the test results remain consistent with the previous results, indicating the robustness of the regression results.

Table 4. Baseline regression results

	(1)	(2)	(3)	(4)	(5)	(6)
	EI	EI	EI	EI	EI	EI

AI	-0.493***	-0.491***	-0.092	-0.259***	-0.267***	-0.073***
	(-15.01)	(-14.94)	(-1.44)	(-6.11)	(-6.22)	(-1.09)
_cons	0.958***	0.958***	1.07***	1.291***	1.029***	1.129***
	(13.08)	(80.26)	(61.70)	(10.05)	(3.92)	(5.02)
Weak tool variable identification	N	N	N	Y	Y	Y
Control variables	N	Y	Y	N	Y	Y
provincial fixed effects	N	N	Y	N	N	Y
Time fixed effects	300	300	300	296	296	296

Note: *, **, *** indicate that the estimated coefficients are significant at the levels of 0.1, 0.05, and 0.01, respectively, and the t-statistics are in parentheses.

5 Conclusions

In this paper, we used panel data from 30 Chinese provinces from 2010 to 2019 to investigate the mechanism of the impact of AI development level on total factor energy efficiency. According to the study's findings, increasing AI level has a positive and significant impact on total factor energy efficiency.

Based on these findings, the following conclusions are drawn in this paper: (1) Hasten the development and promotion of AI policies in the energy sector. Encourage businesses, cities, and countries to use AI technologies to improve energy efficiency and to promote the use of AI in the energy sector. (2) Improve the cultivation of AI talent. Encourage universities and businesses to increase AI talent training and recruitment in order to increase the quantity and quality of talent; and (3) Encourage businesses to invest in energy management systems. The government can encourage businesses to invest in energy management systems by providing financial incentives and other incentives in order to improve energy efficiency, lower energy costs, and reduce pollution; (4) Increase the visibility of intelligent buildings. Encourage businesses and cities to use smart building technologies to improve building energy efficiency and to promote energy conservation and environmental protection; and (5) Support the growth of energy trading markets. Support the growth of the energy trading market and encourage more energy traders to use AI technology to improve the efficiency and security of energy trading; (6) Expand the use of AI in energy policy making.The government should use AI technology in energy policymaking, and formulate more scientific and reasonable energy policies to promote the sustainable use and development of energy through the analysis of energy data and the application of machine learning algorithms.

References

1. Farzaneh H, Malehmirchegini L, Bejan A (2021) Artificial intelligence evolution in smart buildings for energy efficiency. Applied Sciences 11(2): 763.https://doi.org/10.3390/app11020763
2. Sodhro A H, Gurtov A, Zahid N (2020) Toward convergence of AI and IoT for energy-efficient communication in smart homes. IEEE Internet of Things Journal 8(12): 9664-9671.https://doi.org/10.1109/JIOT.2020.3023667
3. Hao X, Wang X, Wu H (2022) Path to sustainable development: Does digital economy matter in manufacturing green total factor productivity? Sustainable Development 31(1):360-378.https://doi.org/10.1002/sd.2397
4. Zhang S, Ma X, Cui Q (2021) Assessing the impact of the digital economy on green total factor energy efficiency in the post-COVID-19 era. Frontiers in Energy Research2021(9): 798922.https://doi.org/10.3389/fenrg.2021.798922
5. Merabet, Ghezlane Halhoul (2021) Intelligent building control systems for thermal comfort and energy-efficiency:A systematic review of artificial intelligence-assisted techniques.Renewable and Sustainable Energy Reviews 144 (2021): 110969.https://doi.org/10.1016/j.rser.2021.110969
6. Li J, Chen L, Chen Y (2022) Digital economy, technological innovation, and green economic efficiency—Empirical evidence from 277 cities in China. Managerial and Decision Economics 43(3): 616-629. https://doi.org/10.1002/mde.3406
7. Liu J, Qian Y, Yang Y (2022) Can artificial intelligence improve the energy efficiency of manufacturing companies? Evidence from china. International Journal of Environmental Research and Public Health 19(4): 2091. https://doi.org/10.3390/ijerph19042091
8. Yu Z, Ren M, Ma L (2022) Effects of Spatial Agglomeration of Digital Economy on Regional Total Factor Energy Efficiency. Economics & Management41(07):28-34.https://oversea.cnki.net/KCMS/detail/detail.aspx?dbcode=CJFD&dbname=CJFDLAST2022&filename=GHZJ202207004&uniplatform=OVERSEA&v=7NjFSP_P96p6mlVJoj8_GOICA3BlUwE7RcGof9q8xcOVv0NKM6RR17p-6B1_jFXF
9. LI T,SHA W (2022) The Impact of Digital Economy on Regional Total Factor Energy Efficiency——Analysis of the Mediating Effect Based on Market Trade. The Theory and Practice of Finance and Economics 2022(03):120-127.https://oversea.cnki.net/KCMS/detail/detail.aspx?dbcode=CJFD&dbname=CJFDLAST2022&filename=CLSJ202203015&uniplatform=OVERSEA&v=dDhEGmkq0XcDMnMZDftnuYe3OYrKrWogtCY7NmJjNTeW7BihhLb1_WpRf0DucPUG
10. XU W, ZHOU J, LIU C (2022) The impact of digital economy on urban carbon emissions:Based on the analysis of spatial effects. Geographical Research 2022(01) :111-129.https://jglobal.jst.go.jp/en/detail?JGLOBAL_ID=202202215433221247