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# The AI Paradox: Assessing the Eco-Efficiency of AI through a Spatial Analysis of Green Total Factor Productivity

**Jing Yang*, Yi Liu, Siyuan Xu, Qianyu Shen**
*College of Economics and Management, Jiangxi Normal University, Nanchang, Jiangxi, China*
**Corresponding Author*

**Abstract: Addressing the critical challenges of environmental degradation and ecological conservation is paramount for achieving sustainable development. Against this backdrop, green total factor productivity (GTFP) has emerged as a crucial indicator for assessing economic performance that internalizes eco-efficiency. Using panel data covering 2010-2019 from 269 prefecture-level and above cities in China, this paper examines how artificial intelligence (AI) influences GTFP and the mechanisms through which it operates. The findings reveal that: (1) AI significantly promotes GTFP locally but inhibits it in neighboring regions due to resource siphoning effects, a conclusion that remains robust to various tests; (2) AI's impact on GTFP exhibits a single-threshold effect, becoming significantly positive only after reaching a certain developmental level; (3) Heterogeneity analyses indicate that AI's positive effects are concentrated in eastern and low-resource-endowment regions; and (4) Mechanism tests confirm that AI enhances GTFP by rationalizing and advancing industrial structure, as well as reducing capital and labour misallocation. These findings provide empirical support for crafting spatially differentiated policies to harness AI's potential in promoting ecological sustainability and green economic transition.**

**Keywords: Artificial Intelligence; Spatial Dubin Model; Industrial Structure; Green Total Factor Productivity; Factor Misallocation**

## 1. Introduction

Against the global backdrop of climate change and environmental degradation, the pursuit of sustainable development has become an urgent worldwide priority. Countries are increasingly seeking pathways to reconcile economic growth with ecological conservation. Green total factor productivity (GTFP), which integrates environmental impacts into efficiency measurements, has emerged as a key indicator for assessing sustainable economic performance. As nations strive to meet their climate and sustainability commitments, outlined in the Paris Agreement and the SDGs set forth by the UN, the role of technological innovation—particularly artificial intelligence (AI)—in enabling a green transition has attracted significant international attention.

China's experience offers a compelling case for examining the interplay between AI and green development. Although China has transitioned to a phase of quality-focused growth, it has yet to fully phase out the legacy economic model characterized by heavy resource dependence, intensive energy use, and significant environmental pollution. With rapid economic growth, resource depletion and environmental pressures have become increasingly severe, intensifying the conflict between development and sustainability. In this context, identifying effective strategies to enhance GTFP is not only critical for China but also offers insights for other economies facing similar challenges.

AI is increasingly acknowledged as a key catalyst for sustainable development. As AI technology progresses and is applied more extensively, the industry has persistently grown. By mid-2023, China's AI landscape was comprised of more than 4,300 enterprises, while its core AI sector had attained a market size valued at RMB 500 billion. In the context of a flourishing digital economy, AI has emerged not just as a crucial driver of swift economic expansion, but also as a key factor to enhance environmental quality. The Action Plan aimed at achieving peak carbon dioxide emissions before 2030 underscores that, guided by carbon objectives, AI serves as a significant tool for promoting innovation-led growth, coordinated advancement, and the green transformation. Despite the strong connections between AI and

sustainable development, there is a scarcity of literature specifically investigating the relationship between AI and GTFP.

Therefore, this study is motivated by the pressing need to identify strategies that can effectively decouple economic activity from environmental harm. Investigating how technological innovation, especially in AI, can accelerate the transition toward a greener economy is thus pivotal for achieving international environmental goals.

This paper seeks to make several marginal contributions to the extant literature, chief among them are three key aspects. First, it offers a theoretical contribution by examining the impact of AI on GTFP, which remains underexplored. The analysis further elucidates the underlying mechanisms through the lenses of industrial structure upgrading and factor misallocation reduction. Second, it provides new empirical evidence. The findings not only confirm a significant single-threshold effect of AI on GTFP but also reveal a spatial spillover effect: while AI development promotes local GTFP after crossing the threshold, it exhibits a restraining effect on GTFP in neighboring regions. Third, on a practical level, this study offers valuable insights for policymakers, suggesting that regions should adopt tailored strategies to foster AI development and enhance GTFP according to their local conditions.

## 2. Literature Review

AI is defined as a machine-based structure that, aimed at specific or general goals, draws conclusions from the data it gathers and produces various outputs, such as predictive insights, contextual information, tailored recommendations, or directives for decision-making, with the ability to impact both physical and virtual environments [1]. Owing to its inherent capacity to revolutionize the paradigms of human-technology interaction, A broad consensus acknowledges AI as a force that is fundamentally reshaping multiple dimensions of economic activity. Specifically, as AI exhibit profound potential in task automation, process streamlining, and resource allocation optimization, it plays a very important impact on industrial structure, labour productivity and employment structure [2]. AI is widely regarded as the potential to fundamentally reshape the economic structure because it is giving rise to novel products, services, and business models [3]. From the perspective of labour productivity, Avezov estimates the labour productivity of international enterprises can be increased by 0-11% through improving the overall equipment effectiveness in manufacturing [4]. From the perspective of employment structure, the task-based framework posits that the creation of new tasks constitutes the predominant driver behind the productivity gains from AI [5].

GTFP revises the conventional total factor productivity (TFP) by systematically internalizing energy and environmental constraints, which highlights the critical importance of managing resource consumption and mitigating ecological impacts within economic growth [6,7]. Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) are the main methods to measure GTFP [8]. DEA method is more commonly used because of its advantages of eliminating the effects of different scales and effectively dealing with multiple outputs and inputs. The method takes the non-desired outputs that negatively affect the environment, such as pollutant emissions, as output variables, combines the directional distance function (DDF) to process the non-desired outputs, and applies the data envelopment analysis to measure GTFP. Xue used the DEA-Malmquist index method to measure the green total factor productivity of resource cities in China [9].

The industrial structure, factor misallocation, urbanization, and economic development are considered as the main influencing factors of GTFP. Upgrading the industrial structure facilitates a transition away from an extensive economic model to an intensive one, thereby enhancing GTFP [10]. In terms of factor misallocation, factor misallocation may lead to inefficient resource utilization and prevent the production process from reaching an optimal state, thus reducing GTFP [11]. In terms of urbanization, the increase of urbanization level can optimize the urban spatial layout, attract the concentration of production factors, enhance resource utilisation efficiency, and thereby promoting growth in total factor productivity [12]. As for economic development, as the level of economic development increases, production factors, excellent talents and advanced green production equipment will be concentrated, which will promote GTFP, but the consumption of resources in the process of economic development will make GTFP decline [13].

Only a small amount of literature has studied the impact of AI on GTFP. Cobbinah point out that digital transformation including AI is recognized as a catalyst for green innovation [14], which optimizes resources and scale green solutions. Chang indicate that AI can reduce the carbon intensity especially in labour-intensive and technology-intensive industries [15]. Industrial structure upgrading and environmental regulation serve as critical pathways through which the digital economy markedly enhances GTFP, as identified in the research of Lyu [16]. Additionally, considering AI is a kind of technological innovation, insights can be drawn from the existing literature on the relationship between technological innovation and GTFP. Wei uncovers a U-shaped relationship between TFP and technological change, manifesting that the benefits materialize only after a certain threshold is reached [17].

Existing studies on AI and GTFP have laid a solid theoretical foundation for this article, but it still remains scope for expansion in this area. First, there is little literature directly examining AI and GTFP. Second, prior research has predominantly analyzed the relationships between AI, industrial structure, and factor misallocation in isolation, or their individual ties to GTFP, but ignore the possible combinability between AI and GTFP may achieve through industrial structure and factor misallocation. Therefore, this study employs panel data covering 2010-2019 from 269 prefecture-level and above cities in China empirically assess the influence of AI development on urban GTFP, which provides theoretical support for the planning of the future application of AI in China as well as the optimisation of high-quality green development of related policies.

## 3. Theoretical Analysis and Research Hypothesis

AI is a new technology that promotes industrial upgrading and technological innovation. According to the theory of technology diffusion, technological innovation can reduce the enterprise's factor consumption and thus increase GTFP. This causal relationship has been empirically validated, with studies demonstrating AI's robust contribution to GTFP growth [18]. As a new technology, AI enables cross-regional technological spillovers. According to the theory of latecomer advantage, due to the imbalance in the level of technological development between cities, cities that are relatively lagging behind in technology tend to adopt and absorb the technological achievements of the advanced cities, and gradually realise technological catching up and transcendence through in-depth learning, active imitation, and continuous innovation and improvement. Specifically, with the increase of exchanges and cooperation between cities, the application of AI in this city will cause other cities to learn and imitate, resulting in the spillover of related technologies. The theory of latecomer disadvantage suggests that due to differences in the level of technological development between cities, cities with relatively backward technologies fall into a vicious circle when imitating the technological achievements of advanced cities, leading to insufficient technological endogeneity and independent innovation. While AI represents an advanced technology, cities that are technologically backward may find themselves constrained by various factors in its application. An excessive focus on technological catch-up could, in fact, exacerbate their challenges. Therefore, the application of AI will have an impact on the neighbouring cities, thus affecting GTFP of the cities. Accordingly, we put forward the following hypothesis:

H1a: AI positively affects the GTFP.

H1b: AI exerts a positive spillover effect on the GTFP of neighboring cities.

H1c: AI generates a negative siphon effect on the GTFP of neighboring cities

The effects of AI potentially follow a non-linear trajectory, as evidenced by Kalai who found identify both symmetric and asymmetric long- and short-run effects of AI on growth across 30 European economies [19]. This non-linearity is further corroborated in environmental research, with [20] demonstrating similar patterns for green efficiency metrics. These findings collectively support the following hypothesis:

H2: There is a non-linear effect of AI on GTFP.

Grounded in discontinuous innovation theory, technological advancement serves as a catalyst for optimization of industrial structure. This process unfolds through two distinct yet complementary pathways: first, by elevating the overall industrial hierarchy (structural advancement), and second, by enhancing resource allocation efficiency and inter-industry linkages (structural rationalization). Empirical evidence confirms that AI actively drives this

dual optimization [21]. Given the established positive relationship between the optimization of industrial structure and GTFP, we propose the following hypothesis regarding the mediating role of industrial structure:

H3a: AI promotes GTFP through industrial advancement.

H3b: AI promotes GTFP through industrial rationalization.

AI also affects factor misallocation. Unlike traditional information technology, AI, as a new generation of information technology, embodies four important techno-economic characteristics, including permeability, creativity, autonomy and substitutability. Firstly, AI is creative and substitutive. In the short term, its integration into economic systems elevates the organic composition of capital, displacing certain labor factors. Long-term adoption, however, fosters emerging intelligent industries that generate employment opportunities, thereby correcting labor misallocation [22]. Secondly, AI has permeability and substitutability, which enables efficient substitution of production factors, releasing redundant resources while enhancing capital utilization [23]. For example, through real-time monitoring technologies like IoT, problems in production can be found and solved in time, and capital utilization efficiency can be improved. As factor misallocation constitutes a recognized barrier to GTFP [24], we postulate the following hypothesis regarding the mediating role of factor misallocation:

H4a: AI promotes GTFP by alleviating capital misallocation.

H4b: AI promotes GTFP by mitigating labour misallocation.

Geographically, in the process of AI application, there is extensive heterogeneity in the level of AI application due to the influence of factors such as the economic development, resource endowments and topography of each region. For example, the eastern region, characterized as capital- and technology-rich but labor-scarce, has adopted AI earlier and now hosts a concentration of intelligent industries. In contrast, the central and western regions, which are labor-rich but deficient in capital and technology, exhibit lower levels of AI adoption and retain a predominance of labor- and resource-intensive industries. In addition, there are differences in natural resources, human resources, technological resources and capital resources in each region, which will lead to obvious differences in the level of AI application in each region. Accordingly, we hypothesize:

H5: The impact of AI on GTFP varies significantly across geographic locations and resource endowment conditions.

## 4. Research Design

### 4.1 Model Construction

4.1.1 Spatial durbin model construction

This paper employs the Spatial Durbin Model (SDM):

$$GTFP_{it}=\alpha_0+\rho\sum_{i=1,i\neq j}^{n}W_{ij}GTFP_{it}+\alpha_1\ln AI_{it}+\sigma\sum_{i=1,i\neq j}^{n}W_{ij}\ln AI_{it}+\alpha_2X_{it}+\tau\sum_{i=1,i\neq j}^{n}W_{ij}X_{it}+\mu_i+\varphi_t+\varepsilon_{it}) \quad (1)$$

Among these, $GTFP_{it}$ denotes GTFP for city i in year t; $\ln AI_{it}$ denotes the logarithm of the number of AI patent applications for city i in year t; $X_{it}$ signifies various control variables; $W_{ij}$ indicates the spatial weight matrix, which consists of both a geographic inverse distance matrix and an economic geography matrix; $\mu_i$, $\varphi_t$ and $\varepsilon_{it}$ represents the city fixed effect, year fixed effect and random disturbance term respectively. $\alpha_0,\alpha_1,\alpha_2$ are the estimated coefficient; $\rho$ represents the spatial correlation of GTFP.

4.1.2 Threshold model construction

To examine potential nonlinear effects of AI on GTFP, we utilize the one-period lagged count of AI patent applications as the threshold variable. Following the panel threshold regression methodology [25], we specify the following model:

$$GTFP_{it}=\gamma_0+\gamma_1\ln AI_{it}I(q_{it}\leq z_1)+\gamma_2\ln AI_{it}I(z_1<q_{it}\leq z_2)+\gamma_3\ln AI_{it}I(q_{it}>z_2)+\gamma_{34}X_{it}+\mu_i+\varphi_t+\varepsilon_{it}) \quad (2)$$

Here, $q_{it}$ is the threshold variable; z is the threshold value; $I(\cdot)$is the indicative function; $\gamma_k$ are the estimated coefficient; other variables are the same as in Eq. (1).

4.1.3 Mediation model construction

On the basis of constructing SDM, we empirically examine whether AI boosts GTFP through the two channels such as the industrial optimization and alleviation of factor misallocation. Employing the two-step mediation analysis method from Jiang [26], we specify the following econometric model:

$$M_{it}=\beta_0+\beta_1\ln AI_{it}+\sigma\sum_{i=1,i\neq j}^{n}W_{ij}\ln AI_{it}+\beta_2X_{it}+\tau\sum_{i=1,i\neq j}^{n}W_{ij}X_{it}+\mu_i+\varphi_t+\varepsilon_{it}) \quad (3)$$

$M_{it}$ denotes the mediating variables, which are industrial optimization (i.e. industrial

advancement and rationalization), factor misallocation (i.e. labour misallocation and capital misallocation); $\beta_k$ are the estimated coefficient; and the rest are the same as in equation (1).

### 4.2 Explanation of Variables

The explained variable in this paper is GTFP. GTFP advances traditional productivity measures by internalizing pollution costs as undesired outputs, offering a more authentic gauge of green development that accounts for both factor input efficiency and environmental impacts. Drawing on the studies of Oh and Heshmati [27], we employ the SBM-GML model to measure GTFP of prefecture-level and above cities. The input indicators selected cover various aspects such as land, labour, capital and energy. Specifically, we measure factor inputs as follows: municipal built-up area (land), urban employment (labor), capital stock computed via the perpetual inventory method (capital), and coal consumption (energy). For outputs, we distinguish between desired and non-desired outputs. Real GDP serves as the desired output proxy, while emissions of sulfur dioxide, industrial wastewater, and soot and dust constitute the non-desired outputs.

The core explanatory variable and threshold variable is AI. Currently, there are four main measures of AI, which are AI patent data, the number of industrial robots, the share of ICT fixed asset investment, and AI comprehensive evaluation index. Industrial robots are more often used in the manufacturing industry, representing a narrower scope, while AI is not limited to manufacturing, but also applied to the service industry, agriculture and other industries. Although AI comprehensive evaluation index can reflect its overall development level, the construction and measurement of the indexes are more cumbersome, and some data are more difficult to obtain. The share of ICT fixed asset investment has a certain bias in the proportion of total investment in social fixed assets, which does not fully represent the level of AI development. AI patent data can measure the level of its scientific and technological output, although there are certain limitations to using patent data, such as the fact that some companies choose not to apply for patents due to commercial confidentiality. In most cases, in order to prevent competing firms from copying or plagiarising their technological innovations, firms should have a strong incentive to apply for patent protection for their innovations. Moreover, the selection of patents using a combination of IPC and keyword searches allows for a more accurate identification and analysis of patents related to AI technology. Therefore, it is reasonable to select AI patent data to represent the level of AI. To ensure the feasibility of a log-linear specification, the AI patent application count is transformed as ln(1 + AI) for all observations to accommodate samples with zero values.

Drawing on the control variables in the existing literature on AI and GTFP, the openness, urbanization, government intervention and economic development are selected as the control variables in this paper. The openness is measured by the ratio of foreign direct investment to real GDP. The urbanization is measured by the ratio of the number of permanent urban residents to the total population of the region. The government intervention is measured by the share of local fiscal expenditure. The economic development is defined as the real GDP per capita and measured in logarithmic terms.

The mechanism variables are industrial structure optimization and factor misallocation. The industrial structure optimization is operationalized through two dimensions, which are rationalization and advancement. Rationalization, captured by the Theil index, reflects coordinated development across sectors, where a lower index denotes a more rational structure. Conversely, advancement, measured by the industrial structure change value, signifies the transition towards a higher-level economic structure, with a higher value indicating greater progress.

In line with Hsieh and Klenow [28], the capital and labor misallocation index is used to indicate factor misallocation.

$$\gamma_{Ki}=\frac{\left(\frac{K_i}{K}\right)}{\left(\frac{s_i\beta_{Ki}}{\beta_K}\right)},\ \gamma_{Li}=\frac{\left(\frac{L_i}{L}\right)}{\left(\frac{s_i\beta_{Li}}{\beta_L}\right)} \tag{4}$$

$$MIS_K=\frac{1}{\gamma_{Ki}}-1,\ MIS_L=\frac{1}{\gamma_{Li}}-1 \tag{5}$$

Here, $\gamma_{Ki}$ and $\gamma_{Li}$ represents the relative distortion coefficients of capital and labour, respectively; $\frac{K_i}{K}$ and $\frac{L_i}{L}$ represent the capital share and the labour share of city i, respectively; $s_i$ is the share of city i's GDP, $\beta_{Ki}$ and $\beta_{Li}$ are the output elasticity of capital and labour. Thus, $\frac{s_i\beta_{Ki}}{\beta_K}$ and $\frac{s_i\beta_{Li}}{\beta_L}$ represent the capital and labour

share and of city i when capital and labor are efficiently allocated. The larger the value of $MIS_K$ and $MIS_L$, the more serious the distortion in the allocation of capital and labour.

### 4.3 Data Sources

We employ panel data covering 2010-2019 from 269 prefecture-level and above cities in China because of the availability and reliability. The patent information is sourced from the Incopat patent database, specifically extracting and organizing patents classified under artificial intelligence using a combination of IPC classification and keyword searches. Economic and social variable data were acquired from a series of China Statistical Yearbook. To mitigate the impact of price fluctuations, all variables related to prices have been adjusted using the GDP index, taking 2006 as the reference year. Table 1 presents the descriptive statistics for the relevant variables.

**Table 1. Descriptive Statistics of Main Variables**

| Variable | Sample size | Mean value | Standard deviation | Minimum value | Maximum value |
|---|---|---|---|---|---|
| GTFP | 2,690 | 1.004 | 0.0500 | 0.488 | 1.633 |
| AI | 2,690 | 2.613 | 1.927 | 0 | 9.719 |
| Industrial rationalization | 2,690 | 0.354 | 3.990 | 0.000146 | 206.9 |
| Industrial advancement | 2,690 | 6.502 | 0.345 | 5.517 | 7.836 |
| Capital misallocation | 2,690 | 0.159 | 0.197 | -0.420 | 1.046 |
| Labour misallocation | 2,690 | -0.0560 | 0.267 | -0.585 | 5.073 |
| Government intervention | 2,690 | 0.202 | 0.129 | 0.00282 | 2.267 |
| Urbanization | 2,690 | 0.550 | 0.146 | 0.0649 | 1 |
| Openness | 2,690 | 0.0174 | 0.0186 | 2.40e-06 | 0.210 |
| Economic development | 2,690 | 10.43 | 0.602 | 8.405 | 12.90 |

## 5. Empirical Analyses

### 5.1 Empirical Analysis based on Spatial Panel Model

**Table 2. Global Moran's Indices for GTFP and AI**

| Year | GTFP | AI |
|---|---|---|
| 2010 | 0.038** | 0.215*** |
| 2011 | 0.085*** | 0.214*** |
| 2012 | 0.012 | 0.207*** |
| 2013 | 0.019 | 0.203*** |
| 2014 | -0.100*** | 0.178*** |
| 2015 | 0.035** | 0.220*** |
| 2016 | 0.080*** | 0.207*** |
| 2017 | 0.071*** | 0.225*** |
| 2018 | 0.166*** | 0.237*** |
| 2019 | 0.017 | 0.217*** |

Note: ** for $p < 0.05$ and *** for $p < 0.01$. The analysis was conducted using Stata.

5.1.1 Spatial autocorrelation test

We test the spatial autocorrelation to justify the application of spatial econometric methods (Table 2). The global Moran's I are significantly for each year for AI while they are statistically significant in all years except 2012 and 2019 for GTFP, which reveals that both AI and GTFP exhibit spatial autocorrelation.

5.1.2 Spatial regression results

First, we test the selection of spatial models (Table 3). The results provide strong support for SDM with two-way fixed effects. The LM test confirms the necessity of a spatial econometric approach while the LR test confirms SDM not SAR or SEM, thus justifying its adoption. Finally, tests for individual and time effects unequivocally support the two-way fixed effects specification.

**Table 3. Selection of Spatial Model**

| Spatial econometric | Coefficient | Spatial measurement model testing | Coefficient |
|---|---|---|---|
| LM-lag | 625.350*** | Wald lag | 10.65*** |
| Robust-LM-lag | 19.220*** | Wald error | 9.16*** |
| LM-error | 617.647*** | Time LR Test | 197.57*** |
| Robust-LM-error | 11.516*** | Space LR Test | 72.77*** |
| LR lag | 24.11*** | Hausman | 34.50*** |
| LR error | 26.3*** | - | - |

Note: * for $p < 0.1$. The analysis was conducted using Stata.

Then, we estimate the SDM using a geographical inverse-distance matrix (Table 4). The significantly positive coefficient of ρ confirms positive spatial spillovers of GTFP across regions. The significantly positive coefficient on lnAI identifies local AI

development as a key driver of GTFP. Conversely, the significantly negative coefficient on W*lnAI implies that AI can inhibit the enhancement of GTFP in neighbouring regions. This finding is similar to Hu [29], which argues the dual nature of AI's impact that are positive locally but negative spatially. The possible reason for this is that while the region achieves productivity enhancement and green technology innovation through AI technology, it will attract high-quality resources including talent and capital from neighbouring regions to cluster in the region, creating a siphoning effect of resources. This siphoning effect may make resources in neighbouring regions scarce, thus inhibiting the improvement of GTFP.

Table 4 also demonstrates the effect of control variables on GTFP. Only the economic development has the significant impact, while the government intervention, the urbanization and the openness do not.

**Table 4. Spatial Regression of AI on GTFP**

| Variable | SDM | GS2SLS | Replace space weight matrix | Replace measure of GTFP |
|---|---|---|---|---|
| lnAI | 0.0026*** | 0.004*** | 0.0025*** | 0.0008*** |
| | (0.0007) | (6.27) | (0.0007) | (0.0003) |
| Government intervention | 0.0066 | 0.021** | 0.0053 | 0.0037 |
| | (0.0085) | (2.54) | (0.0083) | (0.0036) |
| Urbanization | 0.0084 | -0.002 | 0.0105 | 0.0018 |
| | (0.0107) | (0.16) | (0.0104) | (0.0045) |
| Openness | 0.0271 | -0.055 | 0.0315 | 0.0060 |
| | (0.0546) | (1.02) | (0.0541) | (0.0230) |
| Economic development | 0.0077** | 0.010*** | 0.0069** | 0.0034*** |
| | (0.0030) | (3.60) | (0.0030) | (0.0013) |
| W*lnAI | -0.0046** | - | -0.0038** | -0.0017* |
| | (0.0021) | - | (0.0017) | (0.0009) |
| ρ | 0.3803*** | 2.3099** | 0.3449*** | 0.3110*** |
| | (0.0462) | (0.0203) | (0.0399) | (0.0480) |
| sigma2_e | 0.0020*** | - | 0.0021*** | 0.0004*** |
| | (0.0001) | - | (0.0001) | (0.0000) |
| Time fixed | yes | yes | yes | yes |
| Individual fixed | yes | yes | yes | yes |
| N | 2,690 | 2690 | 2690 | 2690 |
| $R^2$ | 0.0015 | 0.0534 | 0.0126 | 0.0003 |

Note: Standard errors in parentheses; * for $p < 0.1$, ** for $p < 0.05$ and *** for $p < 0.01$. The analysis was conducted using Stata.

5.1.3 Endogeneity test

Although the spatial panel model helps overcome certain omitted variable biases to some extent, it may not fully guard against endogeneity arising from reverse causality. While AI plausibly enhances GTFP through knowledge diffusion, cities with higher GTFP levels may also exhibit a greater propensity to adopt AI technology, thus creating an endogeneity problem. To mitigate this endogeneity issue, we employ GS2SLS method for estimation [30]. The persistence of a significant coefficient for AI, as evidenced in Column 2 of Table 4, corroborates the findings from our benchmark regression.

5.1.4 Robustness test

We conduct two robustness checks to validate the baseline results.

(1) To mitigate sensitivity to spatial structure, we replace the geographic inverse distance matrix with an economic geography matrix (Column 3, Table 4).

(2) To mitigate concerns regarding the sensitivity of the results to the GTFP measurement, we recalculate GTFP with the SBM-DDF model (Column 4, Table 4).

The regression from robustness tests remain consistent with the benchmark regression. Therefore, hypotheses H1a and H1c are confirmed while H1b is rejected.

### 5.2 Empirical Analysis based on the Threshold Regression Model

Guided by the Hausman test results that favored fixed effects, we further employ a panel threshold model to investigate potential nonlinearities. Using the one-period lag of AI patent applications as the threshold variable, the

analysis identifies a statistically significant single threshold of 4.7622 at the 5% level, but not for double or triple thresholds (Table 5).

**Table 5. Threshold Effect Test**

| Variable | Threshold | F-value | P-value | Threshold estimate | Threshold value | | |
|---|---|---|---|---|---|---|---|
| | | | | | 10% | 5% | 1% |
| AI | Single threshold | 9.07 | 0.0433 | 4.7622 | 7.4044 | 8.5501 | 11.4869 |
| | Double threshold | 2.17 | 0.8133 | - | 8.4701 | 9.7762 | 14.3562 |
| | Triple threshold | 2.03 | 0.9067 | - | 10.0096 | 11.8177 | 15.9109 |

**Table 6. Empirical Regression Results based on Threshold Value**

| Variable | GTFP |
|---|---|
| lnAI (L.lnAI≤4.7622) | 0.0014<br>(0.0019) |
| lnAI (L.lnAI＞4.7622) | 0.0042**<br>(0.0021) |
| Urbanization | -0.0305<br>(0.0380) |
| Openness | -0.2069**<br>(0.1030) |
| Government intervention | -0.0186<br>(0.0129) |
| Economic development | 0.0211**<br>(0.0102) |
| Constant term | 0.7872***<br>(0.1000) |
| Time fixed | yes |
| Individual fixed | yes |
| N | 2,690 |
| $R^2$ | 0.0626 |

Note: Standard errors in parentheses; ** for $p < 0.05$ and *** for $p < 0.01$. The analysis was conducted using Stata.

Following the identification of a single threshold, we estimate the threshold regression (Table 6). The estimates indicate a statistically insignificant relationship between AI and GTFP when the lagged AI development falls below the threshold. In contrast, a significant positive effect on GTFP emerges once the lagged AI development surpasses this threshold. This finding aligns with the non-linear observation of Fang [31]. A potential interpretation for this pattern is that the initial stage of AI development, hampered by lower technological maturity and a narrower scope of application, hinders its ability to generate a significant, measurable improvement in GTFP. However, once a city's innovative and absorptive capacities breach a critical level, a catalytic cycle begins: accelerated knowledge accumulation enables more profound AI integration. This enhancement facilitates broader and more effective AI integration, thereby strengthening AI's role in promoting GTFP. Thus, hypothesis H2 is confirmed.

## 6. Further Analyses

### 6.1 Mechanism Analysis

The benchmark regression results and robustness test provide evidence to support the assertion that AI will have an impact on GTFP, but there is no specific argument on how AI affects GTFP. Therefore, we conduct the mediation effect test by drawing on the ideas of Jiang [26] on the analysis of the channels of action (Table 7).

First, AI promotes GTFP by fostering a more rational industrial structure. The negative coefficient of lnAI in Column 1 of Table 7 indicates AI contributes to a lower Theil index, signifying promoted coordination among industries. This structural rationalization, in turn, facilitates GTFP enhancement. This finding corroborates earlier work by Hao, who also observe that digitalization reduces the Theil index, implying that digital development fosters inter-industry coordination and thereby advances green development. An explanation is that the application of AI optimises the structure of factor inputs in the production process, prompting various factors to flow across industries, coupled with the permeability of AI to form a strong industrial correlation effect, which promotes the synergistic development of cleaner industries and generalised green industries, leading to reduced energy consumption and less environmental pollution, and ultimately promotes GTFP in the region.

Second, AI enhances GTFP by promoting industrial advancement, as evidenced by the significantly positive relationship between the two in Column 2 of Table 7. Thereby, it suggests that AI contributes to GTFP growth by facilitating industrial structure advancement, a finding that aligns with prior studies. For instance, Gao find that digital technologies can enhance GTFP by facilitating industrial structure advancement. The underlying mechanism involves AI-driven automation and intellectualization of production, which drives a shift of resources into more efficient and emerging industries. Driven by Schumpeter's

creative destruction effect, this transition fosters the growth of new industries while phasing out obsolete production capacities, leading to a reduction in resource waste and lower pollution levels, consequently fostering an improvement in regional GTFP.

Third, AI contributes to GTFP improvement by correcting distortions in capital and labor markets as the effect of AI is significant (Columns 3-4 of Table 7). This resonates with established research, such as the work of Wu, which shows that digital technologies (e.g., the Internet) can enhance GTFP by correcting factor misallocation. A plausible explanation lies in the penetrative nature of AI, which transcends temporal and geographical constraints, thereby enhancing the flexibility of spatial agglomeration and diffusion. With AI development, production factors can be reallocated and recombined across regions according to varying demands, which accelerates cross-regional resource integration. Therefore, the AI development can lead to the reorganization of capital, talent, and other factors beyond regional boundaries, enabling efficient resource integration across different regions in a short period. This process helps alleviate the degree of factor misallocation and ultimately enhances regional GTFP.

Thus, hypotheses H3a, H3b, H4a, and H4b are confirmed.

**Table 7. The Mediating Effect of AI on GTFP**

| Variable | Optimisation of industrial structure | | Factors misallocation | |
|---|---|---|---|---|
| | Industrial rationalization | Industrial advancement | Capital misallocation | Labour misallocation |
| lnAI | -0.3071** | 0.0533*** | -0.0051** | -0.0190** |
| | (0.1383) | (0.0029) | (0.0023) | (0.0079) |
| Government intervention | -0.0707 | 0.1992*** | -0.0654** | 0.0055 |
| | (0.9420) | (0.0354) | (0.0282) | (0.0540) |
| Urbanisation | -0.7710 | 1.1863*** | 0.0313 | -0.1416 |
| | (2.6711) | (0.0446) | (0.0355) | (0.1531) |
| Openness | -12.5254* | 0.0121 | -0.0783 | 1.1107*** |
| | (7.4437) | (0.2284) | (0.1820) | (0.4265) |
| Economic development | 0.4059 | 0.0592*** | 0.0022 | 0.0378 |
| | (0.8351) | (0.0128) | (0.0102) | (0.0479) |
| W*lnAI | 0.2796 | -0.0316*** | 0.0088 | -0.0553** |
| | (0.4604) | (0.0088) | (0.0069) | (0.0269) |
| ρ | -0.0582 | 0.8527*** | 0.3809*** | 0.2062*** |
| | (0.0454) | (0.0286) | (0.0486) | (0.0462) |
| sigma2_e | 14.1227*** | 0.0358*** | 0.0227*** | 0.0464*** |
| | (0.3851) | (0.0010) | (0.0006) | (0.0013) |
| Time fixed | yes | yes | yes | yes |
| Individual fixed | yes | yes | yes | yes |
| N | 2690 | 2690 | 2690 | 2690 |
| $R^2$ | 0.0010 | 0.6135 | 0.1729 | 0.1006 |

Note: Standard errors in parentheses; * for $p < 0.1$, ** for $p < 0.05$ and *** for $p < 0.01$. The analysis was conducted using Stata.

### 6.2 Heterogeneity Analysis

6.2.1 Regional heterogeneity analysis

The impact of AI on GTFP exhibits pronounced regional heterogeneity, being significant only in eastern China (Table 8). This aligns with prior findings like Li [32] who document a stronger influence of the digital economy in the eastern region in China. The disparity stems from asymmetries in AI adoption. The eastern region's more advanced economic development, infrastructure, talent reservoir, and business ecosystem have collectively fostered a more fertile ground for adopting AI, thereby amplifying its impact on GTFP. Furthermore, the region's strategic focus on emerging industries has created an agglomerative effect, attracting high-tech manufacturing and service enterprises to cluster, creating a strong demand for advanced technologies such as AI. Meanwhile, half of the national AI pilot zones are situated in the east, providing significant

impetus for both regional economic vitality and GTFP improvement. In contrast, while central and western China are pursuing a dual strategy of upgrading traditional industries while cultivating emerging sectors, their overall development trajectory continues to lag behind the east due to constraints such as limited resources, geographical disadvantages, industrial structure, and labor costs. Additionally, due to the slow pace of automation (e.g., machine substitution) in the central region and the limited demand for AI in the west, AI's effect on GTFP in the central and western China are insignificant.

**Table 8. Regional Spatial Heterogeneity Analysis**

| Variable | East | Central and West |
|---|---|---|
| lnAI | 0.00475*** (0.00159) | 0.0008 (0.0008) |
| Government intervention | 0.0284 (0.0242) | -0.0012 (0.0084) |
| Urbanization | 0.00919 (0.0243) | -0.0030 (0.0114) |
| Openness | -0.00826 (0.0963) | 0.0279 (0.0683) |
| Economic development | 0.00995 (0.00627) | 0.0082** (0.0033) |
| W*lnAI | -0.00839** (0.00348) | -0.0022 (0.0029) |
| ρ | 0.217*** (0.0602) | 0.3912*** (0.0524) |
| sigma2_e | 0.00281*** (0.000126) | 0.0016*** (0.0001) |
| Time fixed | yes | yes |
| Individual fixed | yes | yes |
| N | 990 | 1700 |
| $R^2$ | 0.0160 | 0.0020 |

Note: Standard errors in parentheses; ** for p < 0.05 and *** for p < 0.01. The analysis was conducted using Stata.

**Table 9. Analysis of Resource Endowment Heterogeneity**

| Variable | High resource-endowed regions | Low resource-endowed regions |
|---|---|---|
| lnAI | 0.000784 (0.00144) | 0.00320*** (0.000992) |
| Government intervention | 0.00490 (0.0143) | 0.00331 (0.0107) |
| Urbanization | 0.00829 (0.0153) | 0.00405 (0.0158) |
| Openness | -0.113 (0.0955) | 0.0858 (0.0660) |
| Economic development | 0.00703* (0.00413) | 0.00691 (0.00447) |
| W*lnAI | -0.00332 | -0.00539* |
| | (0.00356) | (0.00312) |
| ρ | 0.244*** (0.0664) | 0.264*** (0.0529) |
| sigma2_e | 0.00181*** (7.92e-05) | 0.00222*** (7.78e-05) |
| Time fixed | yes | yes |
| Individual fixed | yes | yes |
| N | 1050 | 1640 |
| $R^2$ | 0.022 | 0.036 |

Note: Standard errors in parentheses; * for p < 0.1 and *** for p < 0.01. The analysis was conducted using Stata.

6.2.2 Resource endowment heterogeneity

We categorize the sample into high- and low-resource endowment regions to examine heterogeneity in resource dependence. Table 9 reveals divergent effects of AI on GTFP: the impact is positive and significant in low-resource regions, yet statistically insignificant in high-resource regions. This suggests that regions with lower resource endowment are more capable of leveraging AI technology to enhance GTFP. It may be because of the fact that low-resource endowment regions rely less on traditional resources and thus are more inclined to develop emerging industries and adopt advanced technologies. As a technological innovation, AI not only accelerates the growth of green emerging industries but also reduces resource consumption and environmental pollution through its efficiency and precision. Therefore, the application of AI in low-resource endowment regions can effectively enhance GTFP and promote sustainable development. High-resource regions, conversely, exhibit a high reliance on traditional resources, which contributes to a relatively homogeneous and less diversified industrial structure. Therefore, although the application of AI brings about productivity enhancement and resource consumption reduction to a certain extent, its contribution to GTFP remains limited due to structural constraints within these regions.

Thus, hypothesis H5 is confirmed.

## 7. Conclusion and Policy Implication

This study employs panel data from 269 prefecture-level and above cities in China (2010–2019) to investigate how AI influences GTFP and the mechanisms behind this effect. The key findings are as follows: (1) AI enhances GTFP within the region while having a negative effect on neighboring areas. This conclusion remains consistent after conducting various

robustness tests. (2) A single-threshold effect is observed in the relationship between AI and GTFP; once AI development exceeds this threshold, it exerts a significantly positive influence on GTFP. (3) Analysis of heterogeneity indicates that the beneficial impact of AI is notably significant only in eastern China and in regions characterized by low resource endowment. (4) Further mechanism tests indicate that AI fosters GTFP by through optimizing industrial structure including industrial rationalization and advancement, and alleviating both capital and labour misallocation.

Derived from the empirical results, this research formulates the following policy implications:

First, the government is supposed to promote coordinated development between regions. On the one hand, local governments should work together to formulate detailed and feasible development plans through the establishment of a clear co-operation mechanism, and clarify their respective roles, responsibilities and benefit distribution. On this basis, they should promote resource sharing, technology exchange and market interoperability in order to form a pattern of complementary advantages and synergistic development. On the other hand, the government has the opportunity to create a mechanism for technology transfer that encourages the spread and utilization of advanced AI technologies across various regions. Simultaneously, it is essential to bolster education and vocational training in order to improve the technical proficiency and innovative capability of all areas, ensuring that every region can take advantage of AI technology.

Second, the government should strengthen guidance for AI development. In regions where AI has yet to significantly drive up GTFP, the government should increase investment in order to strengthen the city's infrastructure and ad promote R&D activities to promote the continuous progress and optimisation of AI technology, and to achieve significant technological breakthroughs, which will in turn effectively contribute to GTFP.

Third, the government should formulate strategies for developing AI according to local conditions. For regions with a high level of GTFP, they should leverage their demonstrative role, reduce the siphoning effect of resources between regions, and focus on the radiation effect of AI technology from the core region to the peripheral regions, in order to promote synergistic and balanced development between regions. For regions with low urban GTFP levels, while striving to enhance their own AI development and application, they also need to strengthen external learning and absorptive capacity to more effectively accelerate the improvement of local GTFP.

Fourth, the government should fully leverage all key influencing factors. The government should capitalize on AI's rapid advancement to promote the in-depth integration and synergistic progress of diversified industries and intelligent ecosystems, and build a new industrial system that integrates intelligence, intensification and greening, thereby laying a solid industrial structural foundation for enhancing GTFP. Simultaneously, the government ought to proactively develop and enhance the protection of the market's institutional environment. By creating and enforcing a range of policies and measures, it can alleviate market obstructions and dismantle barriers, thus facilitating the free movement and efficient distribution of resources. This includes, but is not limited to, optimising market access mechanisms, strengthening market regulation, enhancing information transparency and promoting fair competition. Through these measures, the optimal allocation of factors can be further achieved, the degree of marketisation can be enhanced, and favourable conditions can be created for mitigating factor misallocation and thus enhancing GTFP.

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