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*Original Paper*

# How Artificial Intelligence Empowers Regional Low-Carbon Transformation—From the Dual Perspectives of "Carbon Reduction" and "Efficiency Enhancement"

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***Abstract***
*Artificial intelligence is a strategic technology driving the new round of technological revolution and industrial transformation, providing significant impetus for China's high-quality development. This paper employs a two-way fixed effects model and a mediation effect model to empirically analyze AI's impact on regional low-carbon transformation using provincial-level data from China between 2013 and 2022. The findings reveal that AI effectively curbs total carbon emissions while simultaneously boosting green total factor productivity. This conclusion remains robust across a series of stability tests. AI facilitates regional low-carbon transformation by enhancing energy efficiency, accelerating green technological innovation, and accelerating industrial upgrading. The study's conclusions offer significant policy implications for further advancing AI development, leveraging its role in regional emission reduction and efficiency gains, and accelerating high-quality economic development.*
***Keywords***
*Artificial Intelligence, Low-Carbon Transition, Energy Efficiency, Green Technology Innovation, Industrial Structure Upgrading*

## 1. Introduction

The Decision of the Central Committee of the Communist Party of China on Further Comprehensively Deepening Reform and Advancing Chinese Modernization, adopted at the Third Plenary Session of the 20th CPC Central Committee, states: "High-quality development is the primary task in building a modern socialist country in all respects." Regional low-carbon transformation is not only an essential path to achieving high-quality development but also a crucial approach to building a community of life for humanity and nature. Since the reform and opening-up, China has leveraged its endowment advantages to actively integrate into the global value chain, upgrading its industrial structure and improving infrastructure such as transportation and communications. This has enabled historic leaps in economic strength, with growing comprehensive national power and international influence. In 2010, China's GDP surpassed Japan's, making it the world's second-largest economy after the United States. However, precisely because China primarily undertook labor-intensive industries at the lower end of the global value chain—transferred from developed nations—and because most of these transferred industries were characterized by high energy consumption and heavy pollution, coupled with an initial focus on economic growth over environmental pollution control during China's early development phase, issues such as compromised sustainability and environmental degradation have emerged. This demonstrates that China's economic development faces immense pressure for carbon emission reduction and constraints from resource and environmental limitations. At the 75th session of the United Nations General Assembly, General Secretary Xi Jinping made a solemn commitment and for the first time proposed the strategic goals of achieving carbon peak before 2030 and carbon neutrality before 2060. The 2025 Government Work Report also stated: "We will synergistically advance carbon reduction, pollution control, and green growth, accelerating the comprehensive green transformation of economic and social development. Further deepen reforms in the ecological civilization system, coordinate industrial restructuring, pollution control, ecological conservation, and climate change response, and advance development that prioritizes ecology, promotes resource conservation and intensive use, and embraces green and low-carbon practices." Against this backdrop, advancing a comprehensive low-carbon transformation of the economy and society and establishing a green, low-carbon model of high-quality development have become fundamental solutions to ensure achieving carbon peak and carbon neutrality.

Simultaneously, with the continuous innovation of information and communication technologies, artificial intelligence—as a key driver of the new round of technological revolution and industrial transformation[1]—exhibits the spillover characteristics of infrastructure[2]. It not only optimizes capital structure[3], enhances knowledge combination efficiency[4], and mitigates the impact of aging populations[5] to promote economic growth[6], but also boosts corporate productivity by improving factor allocation efficiency, reducing business costs, and strengthening R&D capabilities[7]. Furthermore, AI propels industrial development from deepening division of labor toward mutual integration[8], narrowing the gap in global value chain (GVC) positions between developing and advanced economies while reshaping GVCs in a manner more favorable to developing nations[9]. The Stanford University-published "2025 Artificial Intelligence Index Report" indicates that China maintains dominance in industrial robotics, with 276,300 units installed in 2023—six times Japan's volume and 7.3 times that of the United States—accounting for 51.1% of global market share. China's AI industry reached 404.1 billion yuan in 2021 and surpassed 700 billion yuan in 2024, sustaining over 20% annual growth for consecutive years. This demonstrates the deepening integration of AI across socioeconomic sectors, where its"value creation effect"is reshaping China's economic landscape and emerging as a new driver for structural transformation.

Therefore, how to effectively unleash the propulsive force of AI for regional low-carbon transformation has become an urgent issue to address. Assuming this effect is validated, what differences in characteristics does AI's low-carbon transformation effect exhibit? Furthermore, how does AI empower regional low-carbon transformation, and what are the underlying mechanisms? Answering these questions will help explore feasible pathways for achieving regional low-carbon transformation. Building upon this, accelerating AI development will provide valuable theoretical support for achieving high-quality development in the digital economy era. In light of this, this paper adopts a dual perspective of “carbon reduction” and “efficiency enhancement,” employing an “energy-technology-industry” analytical framework to conduct an in-depth study on the core proposition of AI empowering regional low-carbon transformation. It aims to provide policy basis and theoretical guidance for the Chinese government to develop AI and achieve its “dual carbon” goals amid the new round of technological revolution.

## 2. Literature Review

### *2.1 The Impact of Artificial Intelligence on Carbon Emissions*

Early research on artificial intelligence tended to approach the subject from the perspective of technological progress. Based on conclusions drawn from existing literature, technological progress exerts a dual effect on carbon emissions. On one hand, technological progress exhibits structural effects. As technology advances, it drives industrial restructuring from energy-intensive, high-carbon sectors toward service-dominated tertiary industries. This transition facilitates low-carbon, high-efficiency industrial evolution, thereby reducing carbon emissions. Such studies highlight the positive externalities of technological progress on the environment. Zhang Bingbing[10] and Han Chuan[11] both confirmed through provincial panel data samples in China that technological progress can promote carbon emission reductions. Wang[12] found that energy technology progress lowers carbon intensity by improving energy efficiency and optimizing energy structures. He Bin [13] argued that imitative innovation, as a“follow-up”form of innovation, yields better carbon reduction effects than autonomous innovation. Shen Meng[14] concluded that technological progress has contributed to China's carbon reduction efforts to a certain extent, with eastern and central regions experiencing greater promotion effects than western regions. Wei Weixian[15] demonstrated that coastal areas possess relatively higher technological levels, superior resource distribution, and stronger economic foundations than inland regions, resulting in greater carbon reduction effects from technological progress in eastern coastal areas compared to inland regions. On the other hand, technological progress may also exhibit negative rebound effects on carbon emissions. While it promotes carbon reduction by optimizing resource allocation and enhancing energy efficiency, the efficiency gains generated by technological progress simultaneously create new energy demands. These new demands can even fully offset the energy savings achieved through improved efficiency, ultimately leading to increased carbon emissions. Li Qiang[16] explicitly demonstrate that technological progress enhances energy efficiency, conserving energy consumption and promoting carbon reduction, yet a significant rebound effect persists. Zhang Jiangshan[17], using provincial panel data, found that technological progress failed to reduce energy consumption or lower carbon emissions, instead leading to counterintuitive increases in energy consumption.

Clearly, the impact of technological progress on carbon emissions depends on the combined outcome of these dual effects. Consequently, empirical studies have found the relationship between the two to be uncertain or nonlinear. For instance, Li Kaijie[18] employed a vector error correction model to examine that, in the short term, there is no causal relationship between technological progress and carbon emissions; however, in the long term, technological progress contributes to reducing carbon emissions. Yang Jun[19] analyzed Chinese agricultural data and found that technological progress increases total carbon emissions while reducing carbon intensity. Moreover, the carbon reduction effect of technological progress gradually strengthens as human capital levels rise. Zhang Hua[20] empirically demonstrated an inverted U-shaped relationship between technological progress and carbon emissions in China.

Regarding the primary focus of this paper—the impact of artificial intelligence on carbon emissions—relevant literature remains scarce both domestically and internationally. Xue Fei[21] examined the effects of AI technology on carbon emissions using data from 30 provincial-level regions in China from 2006 to 2019. They found that as AI technology develops, carbon emissions exhibit a distinct pattern of initial increase followed by reduction. Energy utilization efficiency is the primary factor driving the inverted U-shaped relationship between AI technology and carbon emissions. Studies by Zhou[22] and Zhao Yuhan[23] concur that AI facilitates carbon emission reduction, with energy efficiency improvements, green technological advancements, and industrial structure upgrades serving as key mechanisms for promoting carbon emission reduction. ◦

*2.2 The Impact of Artificial Intelligence on Green Total Factor Productivity*

Since Solow introduced the renowned “Solow Paradox” in 1987, scholars have engaged in heated debates over whether artificial intelligence enhances productivity. Some researchers adopt a positive stance on this relationship. Yao Jiaquan[24] empirically demonstrated using micro-enterprise data that AI boosts corporate productivity by reducing demand for routine low-skill labor while increasing demand for non-routine high-skill labor. Du Chuanzhong[7] employed overlapping DID and dual machine learning models to examine that AI significantly enhances China's total factor productivity (TFP) at both macro and micro levels. Li Jincheng[25] research similarly indicates AI boosts TFP without triggering the Solow Paradox.

However, some scholars hold a different view, arguing that an “Solow Paradox” exists between AI and TFP. Specifically, during the early stages of diffusion of general-purpose technologies, productivity growth may experience a prolonged period of stagnation. Cheng Wen[26] examined this from the perspective of general-purpose technology diffusion and found that while AI exhibits a short-term “Solow Paradox,” it effectively boosts TFP in the long run. Sun[27] using Chinese manufacturing data, indicate that AI enhances TFP in traditional manufacturing but has no effect on high-end manufacturing.

This review reveals that existing literature has extensively explored the relationship between carbon emissions and green TFP from an AI perspective. However, several limitations remain: First, theoretical and empirical research has yet to integrate carbon emissions and green TFP within a unified framework. Logically, as a new factor of production, AI's positive externalities and spillover effects can improve energy efficiency, facilitate green technological innovation, and accelerate industrial upgrading, thereby reducing carbon emissions and boosting TFP. Therefore, integrating carbon emissions and green TFP into a unified analytical framework would undoubtedly facilitate a more comprehensive understanding of the intrinsic mechanisms through which AI enables low-carbon transformation. Second, while existing studies have examined the singular channel effects of green technological innovation, energy efficiency, or industrial upgrading on AI's environmental impacts, they have not integrated these three mechanisms into a unified analytical framework to investigate AI's multi-pathway mechanisms for low-carbon transformation. Third, there is a lack of literature exploring the differential characteristics of AI's impact on regional low-carbon transformation from heterogeneous dimensions such as environmental regulations and industrial structure. Based on this, this study constructs a systematic analytical framework for AI's influence on regional low-carbon transformation, with carbon emissions and green TFP as core explanatory variables. It delves into the mechanisms through which AI affects regional low-carbon transformation and examines its heterogeneity at the levels of environmental regulations and industrial structure, thereby addressing gaps in existing literature. This paper's potential contributions lie in three aspects: First, unlike existing studies that separately analyze AI's impact on carbon emissions or green TFP, it comprehensively examines AI's influence on regional low-carbon transformation from both “carbon reduction” and “efficiency enhancement” dimensions, supplementing existing research gaps. Second, it examines AI's role in advancing regional low-carbon transformation through three pathways—energy efficiency, green technological innovation, and industrial upgrading—and empirically tests these mechanisms to identify precise pathways for effective regional low-carbon transition. Third, it addresses the heterogeneity of AI's impact on regional low-carbon transformation, providing decision-making references for formulating targeted low-carbon transition policies.

## 3. Theoretical Analysis and Research Hypotheses

### *3.1 Energy Utilization Effects of Artificial Intelligence*

As a representative of next-generation information technology, artificial intelligence can optimize the allocation of energy resources and enhance energy utilization efficiency, thereby promoting regional low-carbon transformation. From a carbon reduction perspective: First, AI addresses the challenge of decoupling carbon emissions from energy inputs in production processes through precise, dynamic localized control. By leveraging real-time equipment data, energy consumption metrics, and production parameters, it identifies high-carbon segments within energy systems to reduce unnecessary carbon emissions. Second, through systematic, coordinated global optimization, AI enhances renewable energy forecasting accuracy and increases the share of renewable energy, thereby lowering overall carbon emissions at the energy supply end, improving regional energy structures, and achieving structural reductions in regional carbon emissions. From the perspective of "efficiency enhancement": First, AI can analyze enterprise production data in real time, precisely identify misallocations of energy factors, improve output efficiency per unit of energy input, prevent energy waste, and consequently boost enterprises' green total factor productivity. Second, AI can effectively permeate traditional production sectors, reconfiguring the allocation of factors such as energy, capital, labor, and technology. It further strengthens intelligent monitoring and precise forecasting of energy consumption fluctuations and carbon intensity in high-energy-consumption processes. This promotes efficient utilization and green development in industrial production, directing factors like energy, capital, and labor toward high-efficiency, low-carbon sectors. Consequently, it optimizes the structure of factor allocation and ultimately drives regional low-carbon transformation. Based on this, the following research hypotheses are proposed.

Hypothesis 1: Artificial intelligence can promote regional low-carbon transformation by enhancing energy utilization efficiency.

*3.2 The Green Technology Impact of Artificial Intelligence*

Technological advancement serves as a crucial means to address economic and environmental challenges. As a cutting-edge technology of the new generation technological revolution, artificial intelligence possesses both green and technological attributes. The technological progress it brings facilitates pollution reduction, carbon emission cuts, and sustainable development, driving green technological innovation and supporting regional low-carbon transitions. On one hand, AI delivers technological dividends to traditional industries, disrupting conventional industrial R&D models. Enterprises can efficiently integrate innovation factors, accelerate the development and implementation of low-carbon technologies, and shorten their R&D cycles. Simultaneously, with AI assistance, enterprises can optimize application scenarios for low-carbon technologies, reduce reliance on fossil fuels, shift energy structures toward clean sources, and achieve precise carbon reduction. On the other hand, while traditional technological innovation relies on marginal optimization within existing frameworks, AI propels innovation from incremental improvements to breakthrough advancements. By identifying novel innovation points elusive to conventional methods, it directly transforms core production paradigms, enabling qualitative leaps in green total factor productivity. Furthermore, AI accelerates the diffusion and conversion efficiency of innovation outcomes, breaking down information barriers between industries. This facilitates rapid adoption of innovations by enterprises, reduces resource waste from redundant R&D, maximizes the contribution of technological innovation to green TFP, and emphasizes "efficiency gains." Based on this, the following research hypothesis is proposed:

Hypothesis 2: Artificial intelligence can promote regional low-carbon transformation by facilitating green technological innovation.

*3.3 Industrial Structure Effects of Artificial Intelligence*

As a strategic general-purpose technology driving a new wave of technological revolution and industrial transformation, artificial intelligence can effectively promote industrial convergence and the upgrading of industrial structures[8], unlock structural dividends, and advance regional green and low-carbon transitions. From a carbon reduction perspective: First, enterprises can leverage AI-driven intelligent production processes to shift industrial operations from factor-driven to efficiency-driven models. By dynamically regulating production through machine learning algorithms, they reduce redundant energy consumption and unnecessary carbon emissions, thereby advancing industries toward greater efficiency and lower carbon footprints. Second, AI can break down traditional industrial boundaries, fostering cross-sector collaboration and integration to build low-carbon industrial ecosystems. Third, leveraging AI's predictive analytics capabilities, policymakers can train models correlating industrial development trends with carbon emissions to forecast the carbon reduction effects of different industrial adjustment plans. This enables governments and enterprises to effectively avoid resource wastage and carbon emission fluctuations caused by blind transformation, ensuring industrial upgrading consistently advances along a low-carbon trajectory. From an “efficiency enhancement” perspective: On one hand, AI can precisely identify differences in marginal returns to factors across industries and within industrial segments, eliminating information asymmetry in traditional factor allocation. This guides capital, labor, and technology from inefficient sectors to higher-efficiency ones with greater marginal returns, reducing factor misallocation. Underutilized factors are redirected to high-efficiency production activities, boosting total output with fixed factor inputs. On the other hand, AI can dissolve boundaries between industries and promote integrated upgrading, breaking down traditional sectoral silos. This fosters new forms of industrial convergence like “AI+,” reconfiguring value distribution within industrial value chains. The industrial structure shifts from labor- and capital-intensive to technology- and knowledge-intensive sectors, driving overall improvements in green total factor productivity. Based on the above analysis, this paper proposes the following hypothesis:

Hypothesis 3: Artificial intelligence can accelerate regional low-carbon transformation by promoting industrial structure upgrading.

## 4. Empirical Research Design

*4.1 Construction of the Measurement Model*

This paper constructs the following econometric model to empirically examine the impact of artificial intelligence on regional low-carbon transformation:

$$Y_{it} = \alpha_0 + \alpha_1 AI_{it} + \beta X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (1)$$

Here, i denotes province, t denotes year, Y represents the explained variable—total carbon emissions and green total factor productivity—measuring regional low-carbon transition from both carbon reduction and efficiency enhancement dimensions. AI indicates the level of artificial intelligence development. X represents the control variable, $\mu_i$ denotes the province fixed effect, $\gamma_t$ indicates the year fixed effect, and $\varepsilon_{it}$ signifies the random error term.

### *4.2 Variable Declaration*

4.2.1 Dependent Variables

Selecting total carbon emissions and green total factor productivity as dependent variables, regional low-carbon transition is measured from two dimensions: “carbon reduction” and “efficiency enhancement.” On one hand, the natural logarithm of total carbon dioxide emissions serves as a proxy indicator for the “carbon reduction” aspect of regional low-carbon transition. Numerous scholars have proposed various carbon emission calculation methods. Following the 2006 IPCC National Greenhouse Gas Inventory Guidelines, this study adopts the internationally prevalent IPCC methodology: total carbon emissions are represented by the sum of the products of energy consumption and carbon emission factors. This includes nine representative energy sources: raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas (LPG), and natural gas. On the other hand, this study incorporates energy input and carbon emissions into the traditional TFP framework to measure green total factor productivity as the explained variable at the “efficiency gain” level of regional low-carbon transition. Following the methodology of Liu Zhuankuo and Xin Li [28], the GML index based on the SBM directional distance function is used to measure the total factor productivity of China's 30 provinces. Drawing on the research of Li Zhanfeng and Su Wenyuan [29], labor, capital, and energy are selected as input factor indicators. For labor input, the year-end employment figures of each province were used as the measure. For capital input, capital stock was employed as the measure. Drawing on Shan Haojie [30] perpetual inventory method, capital stock was estimated using 2000 as the base year and a depreciation rate of 10.96%. For energy input, the total energy consumption of each province served as the measure. For output indicators, expected output is measured by GDP deflator-adjusted real GDP; unwanted output is measured by each province's carbon dioxide emissions.

4.2.2 Core Explanatory Variable

Industrial robots serve as the primary vehicle for artificial intelligence technology in production processes, providing a relatively accurate reflection of AI application status. Therefore, drawing upon the research of Wang Yongqin[31], this paper constructs a regional industrial robot penetration index using 2004 as the base year, guided by the principles of Bartik's instrumental variables method. The specific formula is as follows:

$$AI_{it} = \sum_{j=1}^{N} \frac{Labor_{ij}^{2004}}{Labor_{i}^{2004}} * \frac{Robot_{jt}}{Labor_{j}^{2004}} \tag{2}$$

In Equation (2), $AI_{it}$ denotes the industrial robot penetration rate in province i during year t, serving as a proxy indicator for artificial intelligence; $Labor_{ij}^{2004}$ represents the employment figure in industry j for province i in China during the base year 2004; $Labor_{i}^{2004}$ denotes the employment figure in industry j for China during the base year 2004; $Robot_{jt}$ indicates the industrial robot installation volume in industry j nationwide during year t; $Labor_{j}^{2004}$ signifies the employment figure in province i during the base year 2004.

4.2.3 Control Variables

The control variables selected for this study include: (1) Degree of openness to the outside world: (Total import and export value of goods×USD/CNY exchange rate) / Regional GDP. (2) Population density: Regional total population / Area of regional administrative divisions. (3) Level of financial development: Ratio of outstanding loans from financial institutions to GDP. (4) Degree of government intervention: General public budget expenditure / Regional GDP. (5) Energy structure: Regional electricity consumption / Total national electricity consumption. (6) Urbanization level: Urbanization rate.

### *4.3 Data Source*

Due to limitations in data availability, this study ultimately selected 30 provinces in China (excluding Hong Kong, Macao, Taiwan, and Tibet) from 2013 to 2022 as the research subjects to examine the impact of artificial intelligence on regional low-carbon transformation. Data sources include the International Federation of Robotics (IFR), the China Statistical Yearbook, the China Energy Statistical Yearbook, and provincial statistical yearbooks. For a small number of missing data points, linear interpolation was employed to fill gaps, and variables underwent truncation processing. Descriptive statistics are presented in Table 1.

**Table 1. Descriptive Statistics**

| Variable Name | Symbol | Sample Size | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|---|---|
| Total Carbon Emissions | Co2 | 300 | 10.471 | 0.794 | 8.616 | 14.461 |
| Green Total Factor Productivity | GTFP | 300 | 1.124 | 0.277 | 0.771 | 2.557 |
| Level of Artificial Intelligence | AI | 300 | 0.212 | 0.135 | 0.025 | 0.872 |
| Degree of Openness to the Outside World | Open | 300 | 0.259 | 0.257 | 0.008 | 1.257 |
| Population Density | Density | 300 | 0.048 | 0.071 | 0.001 | 0.393 |
| Level of Financial Development | Fin | 300 | 1.600 | 0.464 | 0.740 | 3.000 |
| Degree of Government Intervention | Gov | 300 | 0.250 | 0.101 | 0.107 | 0.643 |
| Energy Structure | Energy | 300 | 0.033 | 0.023 | 0.004 | 0.094 |
| Level of Urbanization | Urban | 300 | 0.614 | 0.114 | 0.379 | 0.896 |

## 5. Empirical Results Analysis

### *5.1 Baseline Regression Results*

Columns (1) to (4) in Table 2 present the benchmark regression results for AI's impact on total carbon emissions and total factor productivity after incorporating control variables. Specifically, columns (1) and (2) report AI's effect on total carbon emissions, where the estimated AI coefficient is significantly negative at the 1% level. Columns (3) and (4) report regression results for total factor productivity, where the AI coefficient is significantly positive. The empirical findings indicate that artificial intelligence facilitates regional carbon emission reduction and enhances total factor productivity, thereby advancing China's regional low-carbon transition through dual pathways of carbon reduction and efficiency improvement. Theoretically, as a new form of productive forces driven by technological innovation and intelligent empowerment, AI leverages core technologies such as machine learning and intelligent algorithms to transcend the temporal and spatial constraints of traditional technology integration and knowledge application. It accelerates the precision, efficiency, and intelligent transformation of traditional industries, simultaneously upgrading and optimizing regional industrial structures while increasing demand for renewable energy consumption. This enables the gradual realization of energy consumption reduction effects from structural adjustments, achieving carbon decoupling from industrial structures and thereby advancing regional low-carbon transformation. Other control variables largely align with theoretical expectations.

**Table 2. Basic Regression Results**

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Co2 | Co2 | GTFP | GTFP |
| AI | -0.677*** | -0.482*** | 0.832*** | 0.589*** |
| | (-3.782) | (-3.509) | (4.774) | (3.300) |
| Open | —— | -0.159 | —— | 0.283* |
| | | (-1.051) | | (1.700) |
| Density | —— | 14.699** | —— | 46.796*** |
| | | (2.466) | | (6.859) |
| Fin | —— | -0.110** | —— | -0.077* |
| | | (-2.272) | | (-1.668) |
| Gov | —— | 0.307 | —— | 0.233 |
| | | (1.462) | | (1.084) |
| Energy | —— | 13.663*** | —— | -2.628 |
| | | (3.771) | | (-0.729) |
| Urban | —— | 1.198** | —— | -0.995* |
| | | (2.410) | | (-1.883) |
| _cons | 10.598*** | 8.930*** | 0.938*** | -0.151 |
| | (288.135) | (25.853) | (25.161) | (-0.421) |
| Year | Yes | Yes | Yes | Yes |
| Province | Yes | Yes | Yes | Yes |
| N | 300 | 300 | 300 | 300 |
| $R^2$ | 0.980 | 0.982 | 0.837 | 0.868 |

*5.2 Endogeneity Test*

The primary source of endogeneity issues in this paper likely stems from the bidirectional causality between the dependent variable and the instrumental variable. Specifically, artificial intelligence injects new momentum into regional sustainable development by enhancing energy efficiency, facilitating green technological innovation, and driving industrial upgrading. Simultaneously, numerous technical challenges arise during regional low-carbon transitions, compelling local AI enterprises to overcome technological bottlenecks and thereby address the pain points of low-carbon transformation. Given this, this paper employs the instrumental variables method to test for endogeneity from two perspectives. First, AI is lagged by one period and used as an instrumental variable. The rationale is as follows: Since regional low-carbon transformation in a subsequent period does not retroactively drive local AI development, this partially mitigates endogeneity issues arising from reverse causality. The regression results, presented in Table 3, show that AI coefficients align with the direction of the basic regression for both total carbon emissions and total factor productivity, and are statistically significant at the 5% and 1% levels, respectively. This indicates that AI still promotes regional low-carbon transformation. (2) Following the methodology of Wang Yongqin [32], we constructed an instrumental variable for regional AI levels in China using U.S. industrial robot data. The regression results for this instrumental variable are presented in Table 4. The rationale is as follows: The U.S. ranks among the world leaders in AI development, and its trends reflect the technological evolution direction of the industry. Furthermore, its development timeline closely aligns with China's, satisfying the condition of comparability. Simultaneously, U.S. industrial robot data serves as a sufficiently exogenous instrument variable, exerting no substantive influence on China's natural ecosystems or green low-carbon transition, thus meeting the exogeneity requirement. The specific calculation method is as follows:

$$AI\_US_{it} = \sum_{j=1}^{N} \frac{Labor_{ij}^{2004}}{Labor_{i}^{2004}} * \frac{Robot\_US_{jt}}{Labor\_US_{j}^{1990}} \tag{3}$$

Here, $Robot\_US_{jt}$ denotes the number of industrial robots installed in U.S. industry j in year t, while $Labor\_US_{j}^{1990}$ represents the employment level in U.S. industry j in 1990 (the base year).

**Table 3. Instrumental Variables Regression Results**

| Variables | Instrumental Variables——Co2 | | Instrumental Variables——GTFP | |
|---|---|---|---|---|
| | Phase One | Phase Two | Phase One | Phase Two |
| Lai | 1.049***<br>(20.054) | | 1.049***<br>(20.054) | |
| AI | | -0.435**<br>(-2.065) | | 0.965***<br>(4.873) |
| Control variables | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |

| | | | | |
|---|---|---|---|---|
| City | Yes | Yes | Yes | Yes |
| N | 300 | 300 | 300 | 300 |
| $R^2$ | 0.980 | 0.332 | 0.980 | 0.673 |
| Kleibergen-Paap rk LM | | 55.485*** | | 55.485*** |
| Cragg-Donald Wald F | | 530.179 | | 530.179 |

Columns (1) to (4) in Table 4 present regression results using U.S. industrial robot penetration as an instrumental variable. The first-stage results consistently show that this instrumental variable exhibits a significant positive correlation with the endogenous variable—level of artificial intelligence—thus satisfying the correlation assumption. The second-stage "carbon reduction" results indicate that the AI coefficient is significantly negative at the 5% level, with an increased absolute value compared to the baseline results. This suggests that even after mitigating endogeneity issues through the instrumental variable approach, AI still significantly suppresses regional carbon emissions. The "efficiency gains" results show a significantly positive AI coefficient, with the instrumental variable results further indicating that AI enhances green total factor productivity. Simultaneously, the unidentified Kleibergen-Paap rk LM Sstatistic of 11.522 and the weakly identified Cragg-Donald Wald Fstatistic of 23.371 indicate passing tests for exogeneity and weak instrument identification, confirming the appropriateness of the instrumental variable approach.

**Table 4. Instrumental Variables Regression Results**

| Variables | Instrumental Variables——Co2 | | Instrumental Variables——GTFP | |
|---|---|---|---|---|
| | Phase One | Phase Two | Phase One | Phase Two |
| IV | 25.995*** | | 25.995*** | |
| | (3.664) | | (3.664) | |
| AI | | -1.469** | | 1.689** |
| | | (-2.183) | | (2.170) |
| Control variables | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| City | Yes | Yes | Yes | Yes |
| N | 300 | 300 | 300 | 300 |
| $R^2$ | 0.943 | 0.265 | 0.943 | 0.626 |
| Kleibergen-Paap rk LM | | 11.522*** | | 11.522*** |
| Cragg-Donald Wald F | | 23.371 | | 23.371 |

*5.3 Robustness Test*

5.3.1 Replace Core Explanatory Variables

To further test the robustness of total carbon emissions and green total factor productivity, we adopt an industrial intelligence index that measures AI levels across three dimensions—infrastructure, production applications, and competitiveness and efficiency—following the methodology of Sun Zao and Hou Yulin[33]. Columns (1) and (2) in Table 5 present regression results after replacing the core explanatory variables. It can be observed that after replacing the explanatory variables, artificial intelligence still significantly suppresses regional carbon emissions at the 1% statistical level and enhances green total factor productivity, confirming the robustness of the findings in this paper.

5.3.2 Replace the Explained Variable

Drawing on the research of Cong Jianhui [34], carbon emissions were recalculated and log-transformed. Specifically, emissions boundaries were divided into three major scopes: Scope 1 encompasses direct emissions from the industrial, transportation, and construction sectors; Scope 2 covers indirect emissions from purchased electricity and other sources; and Scope 3 includes other indirect emissions during production and transportation processes. Total factor productivity was recalculated using the SBM-ML model. The regression results are presented in columns (3) and (4) of Table 5. It can be observed that after replacing the dependent variable, artificial intelligence still significantly reduces carbon emissions and enhances total factor productivity at the 1% level, with results remaining robust. ◦

5.3.3 Exclude Municipalities Directly under the Central Government

This paper employs a robustness test by excluding municipalities directly under the central government. Significant economic and social disparities exist across different regions in China. Compared to other provinces, municipalities directly under the central government possess distinct advantages in economic development, policy implementation intensity, and talent accumulation, resulting in substantial differences in artificial intelligence levels. The regression results excluding municipalities are presented in columns (5) and (6) of Table 5. Compared to the baseline results, the significance level of the artificial intelligence coefficient remains unchanged after excluding municipalities, further indicating the robustness of the baseline findings. ◦

**Table 5. Robust Test Regression Results**

| Variables | Replace Core Explanatory Variables | | Replace the explained variable | | Exclude municipalities directly under the central government | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Co2 | GTFP | Co2 | GTFP | Co2 | GTFP |
| AI | -0.017*** | 0.020*** | -0.300*** | 1.591*** | -0.421** | 0.481** |
| | (-5.033) | (5.546) | (-1.989) | (3.945) | (-2.459) | (2.317) |
| Open | 0.172 | -0.109 | 0.158 | 1.668*** | -0.257 | 0.593** |
| | (1.092) | (-0.713) | (1.373) | (3.992) | (-1.164) | (2.240) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Density | 19.069*** | 41.862*** | 4.884 | 39.583*** | 13.977 | 69.579*** |
| | (3.018) | (5.853) | (1.089) | (3.088) | (1.556) | (7.340) |
| Fin | -0.147*** | -0.031 | 0.029 | -0.266** | -0.127** | -0.090* |
| | (-3.073) | (-0.746) | (0.695) | (-2.578) | (-2.391) | (-1.807) |
| Gov | 0.060 | 0.521** | 0.173 | -0.147 | 0.007 | 0.531** |
| | (0.305) | (2.529) | (0.748) | (-0.313) | (0.031) | (2.528) |
| Energy | 15.880*** | -5.224* | 4.043 | -19.627*** | 13.272*** | -3.169 |
| | (5.203) | (-1.681) | (1.360) | (-3.231) | (3.673) | (-0.938) |
| Urban | 1.657*** | -1.564*** | -0.481 | -0.679 | -0.020 | 0.297 |
| | (4.079) | (-3.562) | (-202) | (-0.462) | (-0.024) | (0.368) |
| _cons | 8.535*** | 0.325 | 10.228*** | 0.509 | 10.018*** | -1.178** |
| | (31.163) | (1.028) | (40.599) | (0.579) | (18.045) | (-2.266) |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Province | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 300 | 300 | 300 | 300 | 260 | 260 |
| $R^2$ | 0.984 | 0.885 | 0.977 | 0.849 | 0.980 | 0.873 |

## 6. Analysis of Mechanism of Action

The empirical findings above indicate that artificial intelligence development significantly promotes regional low-carbon transformation and continuously unlocks the benefits of low-carbon governance. How, then, does AI empower regional low-carbon transformation? Based on the preceding theoretical analysis, AI development can influence regional low-carbon transformation through pathways such as enhancing regional energy efficiency, advancing green technologies, and upgrading industrial structures. The following analysis explores these three pathways. First, AI development promotes regional low-carbon transformation by enhancing energy efficiency. To validate this mechanism, energy efficiency is measured using gross energy consumption per unit of GDP, representing the economic output generated from energy input. The regression results in Column (1) and Column (2) of Table 6 indicate that AI statistically significantly enhances regional energy efficiency at the 10% level. Theoretically, enhancing energy efficiency at both macro and micro levels is a key driver for achieving carbon reduction and efficiency gains. AI development can effectively guide regional economic growth from an energy-intensive, high-emission, extensive model toward a green, low-carbon, intensive model. It promotes the large-scale utilization of clean energy and improves energy efficiency, thereby reducing carbon emissions during production processes and enhancing regional carbon emission performance. Thus, improving energy efficiency constitutes the impact mechanism through which AI propels regional low-carbon transformation.

Second, AI development drives urban low-carbon transformation through green technological progress. To validate this mechanism, we measure it using green patent applications per 10,000 people. Table 6, columns (3) and (4), present the regression results, clearly showing that AI significantly promotes regional green technological progress. Theoretically, technological progress—especially green technological progress—is a crucial means to reduce carbon intensity and enhance carbon emission efficiency. AI, with data—possessing both green and technological attributes—as its core production factor, generates technological progress that tends toward green, low-carbon, and energy-saving solutions. Simultaneously, the integrated development of AI and energy-saving low-carbon technologies helps catalyze a new generation of intelligent low-carbon and energy technologies. This, in turn, facilitates green technological progress and promotes economic low-carbon transformation. Thus, green technological progress constitutes the mechanism through which AI drives regional low-carbon transformation.

Finally, AI development propels urban low-carbon transformation by upgrading industrial structures. To validate this mechanism, the structural upgrading effect of AI is measured using a weighted value representing the product of the proportion of tertiary industries and labor productivity across sectors. Results in Table 6, columns (5) and (6), show that the AI coefficient is statistically significant at the 5% level. Overall, AI drives urban industrial upgrading. However, compared to the coefficients for energy efficiency and green technological progress mechanisms, the structural upgrading effect of AI is relatively smaller. In the Chinese context, the integration of AI with traditional industries is a dynamic and gradual process. Simultaneously, the transition of industrial energy structures from reliance on fossil fuels and other traditional energy sources to clean, green, and low-carbon alternatives is relatively slow. This may weaken the structural effect of AI in enabling traditional industry transformation and promoting new industrial development, thereby supporting regional low-carbon transition. Consequently, industrial structure upgrading emerges as the primary mechanism through which AI drives urban low-carbon transformation.

In summary, AI can drive regional low-carbon transformation by enhancing energy efficiency, advancing green technologies, and upgrading industrial structures, with the structural effect playing a relatively minor role.

**Table 6. Mechanism of Action Verification**

| Variables | (1) Energy Utilization Efficiency | | (2) Green technological progress | | (3) Industrial Structure Upgrading | |
|---|---|---|---|---|---|---|
| | FE | IV | FE | IV | FE | IV |
| AI | 3.334* | 22.287*** | 0.667*** | 1.200*** | 0.097** | 0.633** |
| | (1.792) | (3.011) | (4.930) | (2.787) | (2.044) | (2.540) |
| Open | 1.444 | 4.083 | -0.117 | -0.043 | 0.131*** | 0.206*** |
| | (0.684) | (1.569) | (-0.696) | (-0.259) | (4.534) | (3.505) |
| Density | -114.018* | -298.737*** | 16.561** | 11.369 | 1.634 | -3.583 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (-1.747) | (-2.903) | (1.971) | (1.281) | (1.339) | (-1.277) |
| Fin | -0.729 | -2.674** | 0.057* | 0.002 | 0.031** | -0.024 |
| | (-1.492) | (-2.303) | (1.790) | (0.045) | (2.237) | (-0.852) |
| Gov | -11.180*** | -9.188*** | 0.087 | 0.143 | 0.092 | 0.148* |
| | (-4.526) | (-3.657) | (0.598) | (1.027) | (1.548) | (1.936) |
| Energy | -41.783** | -53.943* | -0.138 | -0.480 | -0.762 | -1.106 |
| | (-2.484) | (-1.815) | (-0.111) | (-0.350) | (-1.196) | (-1.123) |
| Urban | -36.818*** | -12.332 | -0.401 | 0.287 | 0.202* | 0.894*** |
| | (-4.825) | (-1.215) | (-0.783) | (0.436) | (1.679) | (2.722) |
| _cons | 37.074*** | 26.545*** | -0.430 | -0.748** | 2.126*** | 1.744*** |
| | (8.091) | (4.475) | (-1.037) | (-2.166) | (31.191) | (11.024) |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Province | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 300 | 300 | 300 | 300 | 300 | 300 |
| $R^2$ | 0.982 | 0.480 | 0.939 | 0.692 | 0.977 | 0.610 |
| F | 11.214 | 15.931 | 10.804 | 22.718 | 8.326 | 43.756 |

## 7. Heterogeneity Analysis

### *7.1 The Impact of Environmental Regulations*

Compared to regions with stringent environmental regulations, areas with lower regulatory intensity impose more lenient requirements on corporate pollutant concentration limits and clean production technology adoption. Businesses in these regions avoid substantial investments in upgrading environmental facilities or implementing advanced pollution control measures, resulting in significantly lower environmental compliance costs. This directly diminishes the intrinsic motivation for enterprises within such regions to proactively pursue low-carbon transformation. Can artificial intelligence drive green and low-carbon transformation in low-regulation areas, thereby achieving green, high-quality development? To address this, this paper measures local environmental regulation intensity using the ratio of completed industrial pollution control investment to industrial value-added. The sample is divided into high-regulation and low-regulation regions based on the median. The results of the grouped regression are shown in columns (1) to (4) of Table 7. Regarding the “carbon reduction” regression results, the estimated coefficient for artificial intelligence is significantly negative in high-regulation regions but not significant in low-regulation regions. Simultaneously, regarding carbon “efficiency gains,” the estimated coefficient for high environmental regulation regions is significantly positive at the 1% level, while that for low environmental regulation regions is significantly negative. These regression results indicate that AI cannot drive carbon reduction and efficiency gains in low environmental regulation regions, but it can promote both in high environmental regulation regions. Overall, AI is more conducive to advancing the low-carbon transition in high environmental regulation regions.

**Table 7. Test Results for Environmental Regulation Heterogeneity**

| Variables | High Environmental Regulation | | Low Environmental Regulation | |
|---|---|---|---|---|
| | CO2 | GTFP | CO2 | GTFP |
| AI | -0.424* | 0.698*** | -0.191 | -0.664** |
| | (-1.697) | (3.460) | (-0.704) | (-2.030) |
| Open | 0.408 | 0.077 | -0.063 | 0.260 |
| | (1.550) | (0.250) | (-0.269) | (1.269) |
| Density | -20.300 | 31.742* | 21.900** | 54.629*** |
| | (-1.127) | (1.888) | (2.448) | (6.449) |
| Fin | -0.205*** | 0.007 | -0.068 | -0.118 |
| | (-2.986) | (0.144) | (-0.601) | (-1.494) |
| Gov | -0.046 | 0.759*** | 0.907* | -0.471 |
| | (-0.177) | (3.293) | (1.677) | (-1.176) |
| Energy | 7.577* | 7.290* | 21.799** | -7.349 |
| | (1.914) | (1.922) | (2.582) | (-1.160) |
| Urban | 3.247*** | -1.652*** | 0.355 | -1.275* |
| | (3.979) | (-2.685) | (0.436) | (-1.933) |
| _cons | 9.314*** | 0.437 | 8.373*** | 0.042 |
| | (16.159) | (0.886) | (14.515) | (0.087) |
| Year | Yes | Yes | Yes | Yes |
| Province | Yes | Yes | Yes | Yes |
| N | 146 | 146 | 149 | 149 |
| $R^2$ | 0.994 | 0.900 | 0.970 | 0.906 |

A possible explanation for the above findings is that in regions with low environmental regulations, businesses face no compelling need for low-carbon technologies due to lax environmental standards. Most prefer to maintain existing production models to control costs rather than proactively explore ways to integrate artificial intelligence with low-carbon technologies. Moreover, for AI to drive low-carbon transformation, enterprises must proactively respond to environmental technology upgrades. However, businesses in such regions face neither strong environmental compliance pressures nor intrinsic demand for low-carbon technological innovation. This makes it difficult for AI to effectively integrate into production processes and fulfill its role in low-carbon governance, thereby hindering the rapid manifestation of its low-carbon enabling effects. Conversely, regions with stringent environmental regulations impose tighter constraints on corporate environmental practices. To comply with these regulations, enterprises must proactively seek technological pathways for low-carbon development. AI advancement provides digital technology support for low-carbon transformation in highly regulated areas, accelerating the integration and innovation of environmental technologies with digital technologies. This promotes green technological progress and enhances energy efficiency. Leveraging the spillover and diffusion effects of technological convergence, AI further facilitates the synergistic development of energy-saving and low-carbon technologies. This reduces carbon emissions per unit of output and enhances carbon performance. Consequently, AI demonstrates relatively stronger promotional effects on low-carbon transformation in regions with stringent environmental regulations.

*7.2 Impact of Industrialization Level*

Regions with high levels of industrialization typically center their industrial systems around capital-intensive and technology-intensive sectors such as heavy chemical industries, high-end equipment manufacturing, or energy processing. These industrial systems are deeply reliant on existing industrial foundations, supply chain capabilities, and endowments of production factors. During regional economic expansion and industrial system optimization, such areas tend to develop structural rigidity patterns anchored in existing industrial frameworks. Over time, this manifests as long-term path dependence and development lock-in effects, ultimately imposing "industrial structure path lock-in constraints" that hinder critical tasks like industrial iteration and upgrading, transitioning from old to new growth drivers, and achieving green and low-carbon transformation. To examine how artificial intelligence (AI) enables regional low-carbon transformation at different levels of industrialization, this study measures local industrialization levels using the ratio of secondary industry output to regional GDP. The sample is divided into high-industrialization and low-industrialization regions based on the median, with grouped regression analysis conducted. Results in Table 8 (1) to (4) show that AI's estimated coefficients are significantly negative for both high- and low-industrialization regions. However, from a productivity perspective, the estimated coefficient for AI is insignificant in the high-industrialization regression group. Conversely, in the low-industrialization group, the coefficient is significantly positive at the 1% level. This indicates that AI development significantly accelerates low-carbon transformation in regions with low industrialization levels. While AI substantially reduces carbon emissions in highly industrialized regions, it does not yield productivity gains.

**Table 8. Test Results for Heterogeneity in Industrialization Levels**

| Variables | High level of industrialization | | Low level of industrialization | |
|---|---|---|---|---|
| | CO2 | GTFP | CO2 | GTFP |
| AI | -0.543*** | -0.276 | -0.533** | 2.105*** |
| | (-2.814) | (-1.245) | (-2.400) | (6.346) |
| Open | 0.501 | 1.080*** | -0.105 | 0.620** |
| | (1.059) | (2.788) | (-0.528) | (2.331) |
| Density | 8.447 | 82.708*** | -2.871 | 16.958* |
| | (0.498) | (6.350) | (-0.489) | (1.949) |
| Fin | -0.163** | -0.128** | -0.025 | -0.027 |

| | | | | |
|---|---|---|---|---|
| | (-2.339) | (-2.494) | (-0.392) | (-0.281) |
| Gov | -0.813 | 0.319 | 0.250 | 0.124 |
| | (-1.365) | (0.638) | (1.114) | (0.456) |
| Energy | 12.014** | -4.841 | 14.662*** | 17.003** |
| | (2.328) | (-1.285) | (3.494) | (2.505) |
| Urban | -3.197 | -3.869*** | 0.925 | -0.224 |
| | (-1.652) | (-3.696) | (1.550) | (-0.284) |
| _cons | 12.271*** | 0.584 | 9.502*** | -0.564 |
| | (10.287) | (0.692) | (20.417) | (-0.954) |
| Year | Yes | Yes | Yes | Yes |
| Province | Yes | Yes | Yes | Yes |
| N | 148 | 148 | 147 | 147 |
| $R^2$ | 0.975 | 0.933 | 0.994 | 0.887 |

From the perspective of path dependency theory, regions with high industrialization levels have long been dominated by heavy and chemical industries and large-scale standardized production, forming deep dependence on traditional production systems and creating lock-in effects. This path dependency imposes significant limitations on the application of artificial intelligence. While AI can reduce carbon emissions through real-time energy monitoring and optimized resource allocation, the poor equipment compatibility and high process modification costs inherent in traditional production systems make it difficult for AI to overcome the core constraints imposed by existing production frameworks on total factor productivity. Consequently, efficiency gains remain limited. In contrast, regions with low industrialization levels feature more flexible industrial structures, predominantly comprising light industry, emerging manufacturing, or service-oriented sectors. These areas lack the path lock-in associated with traditional heavy-asset production systems. When introducing AI, such regions avoid the high costs of retrofitting outdated systems and can directly embed AI across the entire production chain. This approach enables carbon emission reductions through on-demand production and reduced resource waste while rapidly overcoming inefficient production bottlenecks via intelligent upgrades, thereby driving TFP growth. Therefore, while AI can deliver carbon reduction benefits to both regions through energy optimization, path dependence differences mitigate its impact on TFP growth in highly industrialized areas due to lock-in effects from traditional production systems. Conversely, industrial flexibility in less industrialized regions enables AI to achieve dual outcomes: reducing carbon emissions while boosting efficiency.

## 8. Policy Implications and Conclusions

Through theoretical analysis and empirical testing of AI's role in driving regional low-carbon transformation, this study reaches the following conclusions: (1) AI development enhances regional low-carbon governance effectiveness. AI empowers regional low-carbon transition by reducing regional carbon emissions and improving total factor carbon productivity. This conclusion remains robust across multiple tests, carrying significant policy implications for China's pursuit of its dual carbon goals. (2) Mechanism analysis indicates that AI facilitates regional low-carbon transition through pathways such as energy efficiency improvements, green technological progress, and industrial structure upgrading, though the latter plays a relatively minor role. (3) Heterogeneity tests reveal that AI development accelerates low-carbon transition in regions with low industrialization levels. However, constrained by path dependencies on traditional resource-based industries, its impact on low-carbon governance in highly industrialized regions remains limited. Based on these findings, the following policy implications are proposed.

First, accelerate AI development to propel urban low-carbon transformation. Prioritize advancing AI, deepening the integration and innovative application of digital technologies like 5G and big data across energy, environmental sectors, and traditional industries to foster new technologies, industries, and business models relevant to low-carbon fields. Second, accelerate AI-enabled transformation and upgrading of the energy sector to optimize resource allocation, promote large-scale clean energy utilization, and enhance energy efficiency. Finally, drive traditional industries toward digital, networked, and intelligent transformation. Leverage AI to unlock regional green transition potential, harness its enabling role in reducing carbon emissions and improving carbon performance, and cultivate new momentum for China's regional green and low-carbon development.

Second, based on regional environmental regulations and industrial development realities, accelerate the digital transformation of areas with low environmental regulations and high industrialization levels. These regions should seize AI development opportunities, aligning with local industrial structures and resource endowments to comprehensively transform traditional industries across the entire value chain. Enhance the adaptability of AI to regional industrial restructuring under varying environmental regulations and industrialization levels. Accelerate the cultivation of new business models and formats based on emerging digital technologies, expedite technological progress and green innovation, advance low-carbon technological innovation and intelligent transformation in highly industrialized sectors, overcome the structural energy resource “curse,” and continuously unleash the potential of AI to empower regional low-carbon transitions. This will achieve coordinated coexistence between intelligent transformation and green development in regions with low environmental regulations and high industrialization levels.

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