

## Article

# Artificial Intelligence and Carbon Emissions of Manufacturing Enterprises in China

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## Abstract

We examine the relationship between artificial intelligence application and carbon emissions of Chinese manufacturing enterprises. We find that artificial intelligence can suppress the carbon emission intensity of manufacturing enterprises. A one-unit increase in AI leads to an average decline of 0.009 units in carbon emission intensity. Specifically, artificial intelligence boosts corporate green innovation, total factor productivity and analyst supervision among manufacturing enterprises, thereby curbing their corporate carbon emission intensity. Heterogeneity analysis indicates that the inhibitory effect of artificial intelligence is more significant in state-owned enterprises, polluting enterprises, and enterprises with financing constraints. Overall, we offer policy implications for developing countries to balance industrialization progress and climate responsibilities.

**Keywords:** artificial intelligence; carbon emission; manufacturing enterprise; green innovation; total factor productivity; external supervision

## 1. Introduction

As a primary driver of climate change, carbon emissions not only shape global climate patterns, but also reshape economic development pathways [1–4]. The global pattern of carbon emissions is undergoing significant changes, with marked disparities in total emissions and growth trends across countries. These disparities directly influence the negotiation dynamics of international climate governance [5–8]. The international community is engaged in ongoing bargaining over the allocation of emission reduction responsibilities, emphasizing that differences in national conditions must be incorporated into policy considerations [9–12]. This systemic shift has elevated carbon emissions beyond a purely environmental issue, turning it into a critical topic that affects international discourse power. As emission reductions contributed by green technologies become increasingly prominent, carbon governance must be considered holistically within global development [13–19].

As a core sector of global carbon emissions, the manufacturing industry accounts for the dominant share of emissions in the industrial system [20–23]. From the macro perspective of industrial metabolism, carbon emissions from the manufacturing sector present fundamental and large-scale characteristics [21,24,25]. Its total emissions stem not only from its massive production scale, but also from its coverage of the entire value chain, from resource extraction to product delivery. Such systemic emission characteristics make the manufacturing industry a key priority for climate governance. Its emission reduction



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performance directly affects the progress of achieving global carbon peaking and carbon neutrality goals.

However, current academic research on carbon emissions largely adopts a macro-oriented analytical paradigm, with insufficient exploration of the micro-level operation mechanisms of the manufacturing industry [1,2,26]. In practice, decarbonization efforts within manufacturing sectors have long depended on conventional process optimization and energy efficiency upgrading technologies [20–22]. The application of these traditional optimization methods in complicated production systems encounters inherent constraints [21,24,25]. Typical barriers include rigid process layouts, high upfront renovation expenditures and declining marginal emission reduction benefits. Such obstacles form the key restrictions that hinder deeper advancement in industrial carbon mitigation.

As a general-purpose disruptive technology [27–34], artificial intelligence is deeply integrated into the full chains of industrial production, innovation and operation [35–42]. This technology has exerted revolutionary and transformative impacts on nearly all industrial sectors [43–59]. Its application in carbon emission governance still lacks a systematic theoretical framework, as shown in existing literature [28,60–62]. This gap objectively restricts the innovative development of emission reduction driven by digital technology. From the perspective of technological evolution, research on the link between artificial intelligence and carbon emissions is of critical importance. It not only reveals the underlying mechanisms through which emerging technologies contribute to climate governance [63,64], but also may provide innovative technical solutions for global carbon neutrality goals. Against this backdrop, this paper examines the functional mechanisms between artificial intelligence technology and carbon emissions. It aims to uncover the optimization potential of technology-driven emission reduction pathways, providing a scientific basis for carbon governance.

Taking Chinese listed manufacturing enterprises as the research sample, this paper empirically tests the core mechanisms through which artificial intelligence affects carbon emissions. We find that artificial intelligence can suppress carbon emissions of manufacturing enterprises through three channels: technology empowerment, production empowerment, and supervision empowerment. Specifically, artificial intelligence promotes corporate green innovation, total factor productivity, and analyst supervision for manufacturing enterprises, thereby curbing their corporate carbon emission intensity. Further analysis shows that the property nature, polluting attributes, and financial characteristics of enterprises can generate synergistic effects with artificial intelligence.

Our potential contributions are as follows. First, we expand the literature on the economic consequences of artificial intelligence. Existing research on artificial intelligence is largely concentrated in the computer science field [65–73], while related literature in economics research remains insufficient. We combine artificial intelligence with corporate finance, verifying its enabling effect on carbon emission reduction. In doing so, we contribute to the research fields of artificial intelligence and green finance.

Second, we contribute to the literature about antecedent conditions of carbon emissions. Existing studies on carbon emissions mainly focus on the economic consequences of green policies. We confirm that emerging technologies can curb corporate carbon emissions through industrial practices, providing a valuable reference for related research fields.

Finally, we provide new methodological guidance for sustainable development of manufacturing industry. We clarify the critical role of artificial intelligence in promoting green transition of manufacturing industry, providing practical value for governments to formulate differentiated industrial policies.

## 2. Literature Review and Research Hypothesis

### 2.1. Literature Review

In the modern climate governance framework [74–77], carbon emission policies serve as vital regulatory instruments. Their functional mechanisms and practical effects have attracted extensive academic discussions. Existing studies illustrate that policy types, transmission paths and contextual factors interact to form a complex framework for emission reduction. Feng, Zhao and Yan [1] conduct cross-regional comparative research and confirm that carbon emission policies can directly promote emission reduction. Their effects are also significantly moderated by geographical features, and such spatial heterogeneity is largely driven by differences in technological capacity. This technological transmission path is further verified in China's carbon emission trading pilot programs. Shi, Li, Gao and Li [26] adopt the quasi-natural experiment method and prove that carbon quota allocation and trading price signals form the basic conditions for policy implementation. Differences in legal supervision intensity and regional emission density further bring about gradient variations in corporate policy responses. Policy practices at the city level provide solid micro-level evidence for such differentiated effects. Hou, Hu, Liang and Xu [2] analyze low-carbon city pilot projects and find that targeted regulation on high-emission entities can effectively optimize emission structure. This targeted governance mode integrates the strengths of environmental regulation and market incentives. It also facilitates coordinated improvement in institutional settings and market design so as to amplify overall policy efficiency.

Innovative financial instruments play a distinctive role in carbon emission reduction research. Lu, Li and Yang [9] explore carbon neutrality bonds and clarify how green financial products reshape corporate emission behaviors through scale expansion and internal governance improvement. The emission reduction outcomes of such instruments are jointly adjusted by bond features and corporate attributes. The potential greenwashing risks also indicate that market self-discipline should be matched with official policy supervision. The empirical analysis on green credit policies by Lee et al. [78] further enriches research perspectives from the financial field. The results show that such policies can lower the carbon emission intensity of heavily polluting enterprises via capital renewal channels, and the effect becomes more prominent in regions with high financial marketization. Such coordination between policy and finance is echoed in the research of Liu et al. [79] on governmental environmental attention. This study demonstrates that administrative intervention affects corporate carbon emissions through regulations, fiscal guidance and energy transformation. Relevant regulatory effects are more obvious in energy-dependent enterprises and central and western regions. Such findings reflect how regional development status and industrial traits change policy sensitivity.

From the perspective of international experience, the long-term observation of Swedish carbon tax by Martinsson, Sajtos, Stromberg and Thomann [13] and the evaluation of the EU emission trading system by Colmer, Martin, Muuls and Wagner [74] reach consistent conclusions. Market-oriented policies encourage enterprises to upgrade production technology and cut emission intensity without causing industrial relocation or economic recession. Nevertheless, policy stability is easily disturbed by macroeconomic fluctuations. Yu et al. [80] point out that economic uncertainty drives enterprises to make short-term energy choices. Such practical behaviors conflict with the long-term goals of emission reduction policies, which means policy design needs to adapt to different economic cycles.

Corporate governance factors also exert notable influences on policy implementation. Effective carbon emission governance relies on a multi-level policy system. Financial instruments such as green credit and carbon neutrality bonds provide market-oriented incentives [9,78]. Administrative measures, including environmental regulations and tar-

geted supervision, strengthen policy enforcement [2,79]. This systematic framework must fully consider the heterogeneity of regional development, industrial features and corporate characteristics. Rational combination of policy tools and optimized implementation mechanisms can maximize overall emission reduction benefits.

## 2.2. Literature Summary and Research Gap

Current research rarely establishes a complete theoretical system concerning the link between manufacturing intelligent upgrading and carbon emissions. Research conclusions mainly focus on universal corporate characteristics, failing to identify essential differences among subdivided industries in intelligent technology application, energy efficiency improvement and policy adaptation. Thus, they cannot offer precise decision support for the low carbon transformation of core economic sectors. The manufacturing industry represents core national industrial competitiveness, with features including complex product structure, strict production standards and close industrial chain collaboration. Research focusing on the manufacturing industry can summarize unique patterns behind the coordinated development of intelligent upgrading and carbon emission reduction. Therefore, we take Chinese manufacturing enterprises as research samples and analyze mechanisms of artificial intelligence in promoting manufacturing carbon emission reduction.

## 2.3. Artificial Intelligence and Carbon Emissions

The TOE (Technology–Organization–Environment) framework delivers a theoretical perspective for exploring how artificial intelligence shapes corporate carbon emissions. This framework highlights the combined impacts of technological context, corporate organizational context and external environmental context on the adoption and subsequent outcomes of emerging technologies [81–83]. Based on this theoretical foundation, we analyze the potential mechanism of artificial intelligence on carbon emissions along three interrelated perspectives: technological empowerment, production empowerment, and supervision empowerment.

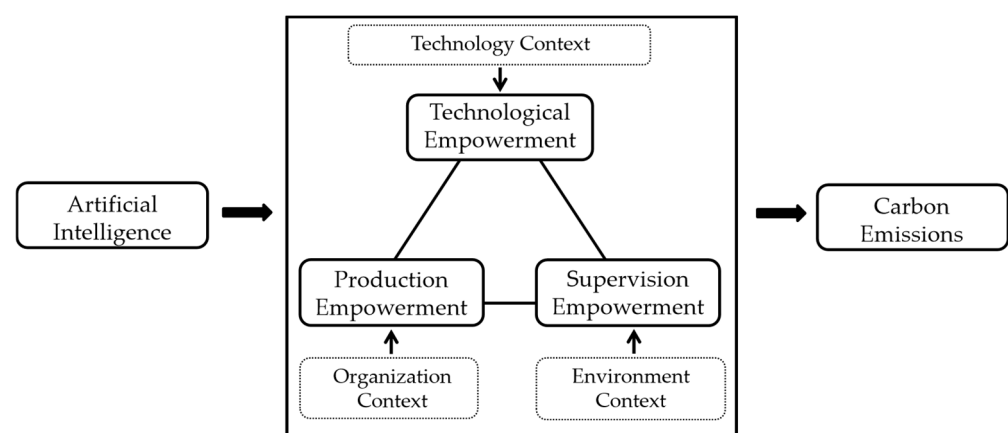
From the perspective of technological empowerment, artificial intelligence can effectively curb carbon emissions by promoting green innovation [28,84,85]. The core mechanism is that artificial intelligence can improve energy utilization efficiency by optimizing manufacturing processes [37,86–88]. In terms of innovation driving force, artificial intelligence accelerates the upgrading and breakthrough of green technologies. It enables enterprises to adopt cleaner production modes and more sustainable material systems [89–98]. Such intelligent green innovation directly cuts down carbon emission intensity in production links.

From the perspective of production empowerment, artificial intelligence can restrict carbon emissions by realizing optimization of production efficiency [99,100]. After artificial intelligence is embedded into production procedures, enterprises can establish closed-loop control systems for energy consumption. They rely on real-time data collection and parameter feedback to realize automatic adjustment of operating thresholds for production equipment [91,101]. At the manufacturing execution level, scheduling algorithms based on deep learning greatly reduce procedure waiting time under traditional production modes [102–104]. The improvement in material circulation efficiency also reduces redundant energy consumption in warehousing links. With the continuous accumulation of production data sets, machine learning models can identify more efficient energy allocation modes [105–107]. Such artificial intelligence-driven transformation of production modes can reshape the carbon emission reduction paths.

From the perspective of supervision empowerment, the adoption of artificial intelligence can raise corporate attention in the capital market and strengthen external con-

straints on corporate carbon emission behaviors. As a popular field of technological investment [90,108], the application of artificial intelligence draws continuous attention from securities analysts and institutional investors [109,110]. Higher market exposure makes corporate environmental performance subject to more intensive public supervision. Environmental performance has become a vital reference for investment decisions [111,112]. When enterprises gain extra market attention through artificial intelligence layout, their deficiencies in environmental governance will face stricter inspection. Carbon emission, as a highly quantifiable environmental indicator, will become a key target of corporate regulation. The supervision enhancement brought by popular technological trends urges enterprises to convert efficiency gains from artificial intelligence into practical emission reduction actions so as to meet capital market expectations for technology-enabled sustainable development.

Based on the above theoretical analysis, this study puts forward the core research hypothesis (as shown in Figure 1).



**Figure 1.** Artificial intelligence and carbon emissions: TOE research framework.

**H1.** *Artificial intelligence can significantly inhibit carbon emissions of manufacturing enterprises.*

### 3. Research Design

#### 3.1. Data Source

We select Chinese listed manufacturing enterprises from 2010 to 2022 as research samples. We collect corporate carbon emission data and control variable data from CS-MAR (China Stock Market & Accounting Research Database). Following relevant existing studies [113,114], we count the frequency of artificial-intelligence-related keywords (as shown in Appendix A and Table A1) disclosed in corporate annual reports. We exclude observations with missing core variables and samples labeled as ST enterprises. Finally, we obtain 19,637 firm-year observations covering 2886 manufacturing enterprises.

#### 3.2. Variable Description

The independent variable in this study is artificial intelligence (AI, as shown in Table 1). Annual reports serve as mandatory disclosure documents for listed enterprises. Each enterprise truthfully discloses operational information covering artificial intelligence R&D (research and development), production line transformation and intelligent business deployment. Enterprises with wider practical application of artificial intelligence tend to mention relevant keywords more frequently in disclosures. Therefore, keyword frequency can act as a valid proxy variable for the corporate artificial intelligence development level. Nevertheless, there remains a possibility that keyword disclosure intensity does not fully align with the actual depth and scale of artificial intelligence application within enterprises. To mitigate measurement bias caused by a single textual indicator, this study further adopts

two alternative indicators, corporate artificial intelligence investment and artificial intelligence patents in robustness tests. Supplementary measurement methods can strengthen the reliability and stability of the research conclusions.

**Table 1.** Variable definition.

| Type                 | Variable  | Definition                                                                   |
|----------------------|-----------|------------------------------------------------------------------------------|
| Dependent variable   | CE        | Corporate carbon emissions/(corporate operating revenue/10,000)              |
| Independent variable | AI        | Natural logarithm of artificial intelligence keyword quantity after adding 1 |
| Control variable     | Size      | Natural logarithm of total assets                                            |
|                      | Lev       | Total liabilities/total assets                                               |
|                      | ROA       | Market value/book value                                                      |
|                      | Cash      | Cash and cash equivalents/total assets                                       |
|                      | Growth    | Growth rate of operating revenue                                             |
|                      | SOE       | Equals 1 if the enterprise is state-owned, otherwise 0                       |
|                      | AT        | Total asset turnover ratio                                                   |
|                      | Age       | Natural logarithm of enterprise establishment years plus 1                   |
|                      | Dual      | Equals 1 if the chairman concurrently serves as CEO, otherwise 0             |
|                      | Top_1     | Shareholding ratio of the largest shareholder                                |
|                      | Board     | Natural logarithm of board member quantity                                   |
|                      | Indeboard | Number of independent directors/total number of board members                |

Note: Corporate carbon emissions = (corporate total operating costs/main operating costs of the industry)  $\times$  industry carbon emissions.

The dependent variable refers to carbon emission intensity, marked as CE, calculated as total corporate carbon emissions divided by operating revenue. Other detailed definitions of control variables are presented in Table 1.

### 3.3. Model Setting

We construct the following OLS regression model to explore the influence of artificial intelligence on carbon emissions of manufacturing enterprises.

$$CE_{i,t} = \beta_0 + \beta_1 AI_{i,t} + Controls_{i,t} + \sum Year_t + \sum Industry_{i,t} + \varepsilon_{i,t} \quad (1)$$

In Formula (1), CE represents carbon emission intensity and AI denotes artificial intelligence level. Controls refer to a set of selected control variables. We further incorporate industry fixed effects and year fixed effects into the regression. In addition, we cluster standard errors at the firm–year level.

## 4. Results

### 4.1. Descriptive Statistics

Table 2 presents the descriptive statistical results of all variables. The mean value of the explained variable CE, which stands for carbon emission intensity, is 0.418, with a minimum value of 0.037 and a maximum value of 2.286. Such figures reveal obvious differences in carbon emission levels among different enterprises. The explanatory variable AI reflects the corporate artificial intelligence development level. Its mean value is 0.254, with a minimum value of 0 and a maximum value of 2.773. This result shows that artificial intelligence application status varies greatly across the sampled enterprises.

**Table 2.** Descriptive statistics.

| Variable  | Num.   | Ave.   | Std.  | Min.   | Med.   | Max.   |
|-----------|--------|--------|-------|--------|--------|--------|
| CE        | 19,637 | 0.418  | 0.556 | 0.037  | 0.139  | 2.286  |
| AI        | 19,637 | 0.254  | 0.578 | 0.000  | 0.000  | 2.773  |
| Size      | 19,637 | 22.003 | 1.150 | 20.025 | 21.818 | 25.659 |
| Lev       | 19,637 | 0.362  | 0.181 | 0.048  | 0.350  | 0.770  |
| ROA       | 19,637 | 0.057  | 0.059 | −0.145 | 0.053  | 0.237  |
| Cash      | 19,637 | 0.054  | 0.064 | −0.119 | 0.052  | 0.239  |
| Growth    | 19,637 | 0.170  | 0.297 | −0.397 | 0.125  | 1.552  |
| SOE       | 19,637 | 0.256  | 0.437 | 0.000  | 0.000  | 1.000  |
| AT        | 19,637 | 0.679  | 0.364 | 0.151  | 0.605  | 2.311  |
| Age       | 19,637 | 2.866  | 0.335 | 1.792  | 2.890  | 3.497  |
| Dual      | 19,637 | 0.345  | 0.475 | 0.000  | 0.000  | 1.000  |
| Top_1     | 19,637 | 0.340  | 0.142 | 0.090  | 0.321  | 0.724  |
| Board     | 19,637 | 2.107  | 0.187 | 1.609  | 2.197  | 2.565  |
| Indeboard | 19,637 | 37.608 | 5.284 | 33.330 | 33.330 | 57.140 |

Note: Num., Ave., Std., Min, Med., and Max. denote sample number, mean, standard deviation, minimum, median, and maximum, respectively.

#### 4.2. Correlation Analysis

Table 3 reports the correlation analysis results for the main variables. The correlation coefficient between AI and CE is −0.185, which is significant at the 1% level. This indicates a significant negative correlation between artificial intelligence and carbon emissions. In addition, the absolute values of the correlation coefficients between all variables do not exceed the empirical critical value of 0.7, indicating that there is no severe multicollinearity among the variables.

**Table 3.** Correlation analysis.

|           | CE         | AI         | Size       | Lev        | ROA        | Cash       | Growth     |
|-----------|------------|------------|------------|------------|------------|------------|------------|
| CE        | 1.000      |            |            |            |            |            |            |
| AI        | −0.185 *** | 1.000      |            |            |            |            |            |
| Size      | 0.127 ***  | 0.065 ***  | 1.000      |            |            |            |            |
| Lev       | 0.125 ***  | 0.012 *    | 0.532 ***  | 1.000      |            |            |            |
| ROA       | −0.065 *** | −0.045 *** | −0.049 *** | −0.391 *** | 1.000      |            |            |
| Cash      | 0.013 *    | −0.049 *** | 0.080 ***  | −0.148 *** | 0.475 ***  | 1.000      |            |
| Growth    | −0.001     | −0.010     | 0.055 ***  | 0.066 ***  | 0.302 ***  | 0.008      | 1.000      |
| SOE       | 0.140 ***  | −0.068 *** | 0.295 ***  | 0.236 ***  | −0.130 *** | −0.039 *** | −0.052 *** |
| AT        | 0.183 ***  | −0.066 *** | 0.167 ***  | 0.236 ***  | 0.205 ***  | 0.163 ***  | 0.172 ***  |
| Age       | 0.029 ***  | 0.065 ***  | 0.209 ***  | 0.142 ***  | −0.084 *** | 0.073 ***  | −0.109 *** |
| Dual      | −0.089 *** | 0.069 ***  | −0.177 *** | −0.127 *** | 0.059 ***  | −0.008     | 0.034 ***  |
| Top_1     | 0.026 ***  | −0.067 *** | 0.072 ***  | −0.017 **  | 0.136 ***  | 0.095 ***  | −0.011     |
| Board     | 0.092 ***  | −0.092 *** | 0.228 ***  | 0.127 ***  | −0.015 **  | 0.016 **   | 0.001      |
| Indeboard | −0.061 *** | 0.053 ***  | −0.001     | −0.004     | −0.013 *   | 0.000      | −0.009     |

Continued Table

|           | SOE        | AT         | Age        | Dual       | Top_1      | Board      | Indeboard |
|-----------|------------|------------|------------|------------|------------|------------|-----------|
| SOE       | 1.000      |            |            |            |            |            |           |
| AT        | 0.086 ***  | 1.000      |            |            |            |            |           |
| Age       | 0.127 ***  | 0.007      | 1.000      |            |            |            |           |
| Dual      | −0.260 *** | −0.071 *** | −0.073 *** | 1.000      |            |            |           |
| Top_1     | 0.106 ***  | 0.133 ***  | −0.096 *** | 0.007      | 1.000      |            |           |
| Board     | 0.240 ***  | 0.055 ***  | 0.010      | −0.165 *** | −0.043 *** | 1.000      |           |
| Indeboard | −0.055 *** | −0.024 *** | 0.023 ***  | 0.097 ***  | 0.061 **   | −0.574 *** | 1.000     |

Note: \*\*\*, \*\*, \* indicate significant statistical significance at 1%, 5%, and 10%, respectively.

#### 4.3. Main Regression

Table 4 reports the baseline regression (Formula (1)) results concerning the relationship between artificial intelligence and carbon emissions of manufacturing enterprises. The goodness of fit of all columns stays above 90%. Column (1) only controls for year and industry fixed effects. Column (2) further incorporates control variables related to corporate characteristics. Column (3) adds more control variables reflecting corporate governance features. Column (3) shows that a one-unit increase in AI leads to an average decline of 0.009 units in the carbon emission intensity. The empirical results show that the regression coefficient of AI remains significantly negative in all specifications. This finding indicates that artificial intelligence can effectively curb the carbon emissions of manufacturing enterprises, which fully verifies Hypothesis H1.

**Table 4.** Main regression: artificial intelligence and carbon emissions of manufacturing enterprises.

|                    | (1)<br>CE              | (2)<br>CE               | (3)<br>CE               |
|--------------------|------------------------|-------------------------|-------------------------|
| AI                 | −0.006 ***<br>(−4.639) | −0.009 ***<br>(−6.709)  | −0.009 ***<br>(−6.599)  |
| Size               |                        | 0.002<br>(1.446)        | 0.002<br>(1.607)        |
| Lev                |                        | 0.031 ***<br>(3.532)    | 0.032 ***<br>(3.602)    |
| ROA                |                        | −0.531 ***<br>(−18.653) | −0.537 ***<br>(−18.724) |
| Cash               |                        | −0.134 ***<br>(−6.093)  | −0.134 ***<br>(−6.130)  |
| Growth             |                        | −0.021 ***<br>(−4.286)  | −0.020 ***<br>(−4.108)  |
| SOE                |                        | 0.013 ***<br>(4.885)    | 0.013 ***<br>(4.495)    |
| AT                 |                        | 0.083 ***<br>(19.081)   | 0.081 ***<br>(18.774)   |
| Age                |                        | 0.014 ***<br>(3.415)    | 0.015 ***<br>(3.651)    |
| Dual               |                        |                         | −0.004 **<br>(−1.970)   |
| Top_1              |                        |                         | 0.024 ***<br>(2.930)    |
| Board              |                        |                         | −0.018 ***<br>(−2.602)  |
| Indeboard          |                        |                         | −0.000<br>(−0.995)      |
| Constant           | 0.525 ***<br>(60.172)  | 0.422 ***<br>(16.161)   | 0.457 ***<br>(14.607)   |
| Fixed effect       | Yes                    | Yes                     | Yes                     |
| N                  | 19,637                 | 19,637                  | 19,637                  |
| Adj.R <sup>2</sup> | 0.924                  | 0.931                   | 0.931                   |

Note: \*\*\*, \*\* indicate significant statistical significance at 1%, 5%, respectively.

#### 4.4. Endogeneity Test: Instrumental Variable Method

The Chinese State Council issued official documents to launch the Broadband China strategy in 2013. Several batches of demonstration cities were successively established from 2014 to 2016 to accelerate the construction of new infrastructure such as urban optical fiber networks. This strategy improves network bandwidth and reduces communication delay. It builds reliable data transmission conditions for enterprises to deploy machine learning

algorithms and train artificial intelligence models, and supports the practical application of mainstream intelligent technologies [101,115,116]. The strategy thus exerts vital driving effects on the development of corporate artificial intelligence.

The selection of demonstration cities is independent of individual corporate decisions, which ensures the exogeneity of this policy [28,116,117]. In addition, this policy mainly focuses on upgrading urban information infrastructure. Its policy framework does not include direct rules, subsidies or evaluation standards targeting corporate carbon emission governance. This policy cannot directly change an enterprise's energy consumption structure, emission reduction choices or carbon management behaviors via administrative or market-based tools. Moreover, broadband networks act as general basic infrastructure. They can only improve an enterprise's production efficiency and environmental performance when matched with specific technologies such as artificial intelligence [28,116,117]. Therefore, Broadband China policy meets the exclusion restriction requirement for qualified instrumental variables.

This study defines the dummy variable Broadband. The value equals 1 if an enterprise is located in designated demonstration cities and the observation year falls in or after the official establishment year, otherwise 0. Column (1) of Table 5 proves that the Broadband China strategy significantly boosts the development of corporate artificial intelligence. Column (2) shows that the fitted artificial intelligence variable AI\_fitted can notably curb carbon emissions.

**Table 5.** Endogeneity test: instrumental variable.

|           | (1)<br>AI              | (2)<br>CE               |
|-----------|------------------------|-------------------------|
|           | First Stage            | Second Stage            |
| Broadband | 0.071 ***<br>(8.468)   |                         |
| AI_fitted |                        | −0.177 ***<br>(−5.320)  |
| Size      | 0.056 ***<br>(12.195)  | 0.012 ***<br>(5.088)    |
| Lev       | −0.097 ***<br>(−3.431) | 0.015<br>(1.572)        |
| ROA       | −0.253 ***<br>(−2.642) | −0.581 ***<br>(−19.370) |
| Cash      | −0.178 ***<br>(−2.612) | −0.166 ***<br>(−7.212)  |
| Growth    | −0.051 ***<br>(−3.616) | −0.028 ***<br>(−5.558)  |
| SOE       | −0.019 **<br>(−2.053)  | 0.010 ***<br>(3.496)    |
| AT        | 0.021 **<br>(1.982)    | 0.085 ***<br>(19.368)   |
| Age       | −0.067 ***<br>(−4.903) | 0.004<br>(0.827)        |
| Dual      | 0.027 ***<br>(3.267)   | 0.000<br>(0.108)        |
| Top_1     | −0.093 ***<br>(−3.519) | 0.009<br>(1.000)        |
| Board     | −0.064 **<br>(−2.258)  | −0.030 ***<br>(−4.027)  |
| Indeboard | −0.001<br>(−1.257)     | −0.000 *<br>(−1.684)    |
| Constant  | −1.000 ***<br>(−8.601) | −0.022<br>(−0.465)      |

**Table 5.** *Cont.*

|                                     | (1)<br>AI   | (2)<br>CE    |
|-------------------------------------|-------------|--------------|
|                                     | First Stage | Second Stage |
| Fixed effect                        | Yes         | Yes          |
| N                                   | 19,637      | 19,637       |
| Cragg–Donald Wald F statistic       |             | 71.778       |
| Kleibergen–Paap rk Wald F statistic |             | 72.019       |
| Adj.R <sup>2</sup>                  | 0.233       | 0.931        |

Note: \*\*\*, \*\*, \* indicate significant statistical significance at 1%, 5%, and 10%, respectively.

We further perform a series of robustness checks to verify the validity of the IV regression. Specifically, we employ Kleibergen–Paap rk LM statistics to verify the correlation between Broadband and AI. The results presented in Table 5 indicate that the two F-tests both confirm that Broadband is not a weak instrumental variable.

#### 4.5. Endogeneity Test: Propensity Score Matching

We split the full sample into treatment and control groups according to the median value of AI. We carry out 1:1 nearest neighbor matching with all control variables set as matching covariates. Regression tests are then implemented based on the matched sample (Table 6). The coefficient of AI maintains statistical significance, mitigating the endogeneity bias existing between artificial intelligence and carbon emissions.

**Table 6.** Endogeneity test: propensity score matching.

|                    | (1)<br>CE              | (2)<br>CE               |
|--------------------|------------------------|-------------------------|
| AI                 | −0.007 ***<br>(−3.864) | −0.008 ***<br>(−4.575)  |
| Size               | −0.002<br>(−1.118)     | 0.001<br>(0.284)        |
| Lev                | 0.057 ***<br>(3.198)   | 0.041 ***<br>(2.951)    |
| ROA                | −0.418 ***<br>(−8.114) | −0.450 ***<br>(−11.315) |
| Cash               | −0.106 ***<br>(−3.152) | −0.088 **<br>(−2.512)   |
| Growth             | −0.022 ***<br>(−3.260) | −0.029 ***<br>(−4.898)  |
| SOE                | 0.008 *<br>(1.803)     | 0.013 ***<br>(2.805)    |
| AT                 | 0.082 ***<br>(12.750)  | 0.077 ***<br>(12.108)   |
| Age                | 0.018 ***<br>(3.145)   | 0.017 ***<br>(2.900)    |
| Dual               |                        | −0.009 **<br>(−2.559)   |
| Top_1              |                        | 0.025 **<br>(2.119)     |
| Board              |                        | −0.013<br>(−1.538)      |
| Indeboard          |                        | −0.000<br>(−1.370)      |
| Constant           | 0.385 ***<br>(9.496)   | 0.435 ***<br>(8.826)    |
| Fixed effect       | Yes                    | Yes                     |
| N                  | 8038                   | 8038                    |
| Adj.R <sup>2</sup> | 0.938                  | 0.937                   |

Note: \*\*\*, \*\*, \* indicate significant statistical significance at 1%, 5%, and 10%, respectively.

#### 4.6. Robustness Test

##### 4.6.1. Change the Measurement Method of Artificial Intelligence

This section adopts the ratio of artificial intelligence investment to assets as a new proxy variable (AI2) [28]. The corresponding regression results are presented in Column (1) of Table 7. The coefficient of AI2 remains significantly negative.

**Table 7.** Robustness test.

|                    | (1)<br>CE               | (2)<br>CE              | (3)<br>CE2                | (4)<br>CE               | (5)<br>CE               |
|--------------------|-------------------------|------------------------|---------------------------|-------------------------|-------------------------|
| AI2                | −0.472 ***<br>(−4.126)  |                        |                           |                         |                         |
| AI3                |                         | −0.007 ***<br>(−7.678) |                           |                         |                         |
| AI                 |                         |                        | −0.024 ***<br>(−4.171)    | −0.010 ***<br>(−4.992)  | −0.005 **<br>(−2.321)   |
| Size               | 0.001<br>(1.192)        | 0.006 ***<br>(4.509)   | 0.998 ***<br>(259.025)    | 0.001<br>(0.928)        | 0.004<br>(0.834)        |
| Lev                | 0.035 ***<br>(3.749)    | 0.051 ***<br>(5.919)   | 0.586 ***<br>(16.027)     | 0.030 ***<br>(3.007)    | 0.030 *<br>(1.728)      |
| ROA                | −0.516 ***<br>(−17.152) | −0.287 ***<br>(−9.536) | −1.255 ***<br>(−9.167)    | −0.575 ***<br>(−16.348) | −0.442 ***<br>(−11.131) |
| Cash               | −0.134 ***<br>(−5.732)  | −0.056 **<br>(−2.569)  | 0.208 ***<br>(3.749)      | −0.088 ***<br>(−3.395)  | −0.125 ***<br>(−4.311)  |
| Growth             | −0.018 ***<br>(−3.682)  | −0.007<br>(−1.208)     | −0.139 ***<br>(−6.531)    | −0.012 **<br>(−2.315)   | −0.013 **<br>(−2.242)   |
| SOE                | 0.015 ***<br>(5.213)    | 0.016 ***<br>(4.985)   | 0.058 ***<br>(8.384)      | 0.011 ***<br>(3.598)    |                         |
| AT                 | 0.081 ***<br>(17.197)   | 0.045 ***<br>(9.078)   | 1.497 ***<br>(118.522)    | 0.077 ***<br>(16.307)   | 0.041 ***<br>(3.552)    |
| Age                | 0.015 ***<br>(3.433)    | 0.001<br>(0.319)       | 0.121 ***<br>(8.616)      | 0.011 **<br>(2.254)     | −0.022<br>(−0.733)      |
| Dual               | −0.003<br>(−1.199)      | 0.000<br>(0.032)       | −0.022 ***<br>(−3.318)    | −0.007 **<br>(−2.539)   | 0.002<br>(0.549)        |
| Top_1              | 0.023 ***<br>(2.759)    | 0.014 *<br>(1.690)     | 0.099 ***<br>(4.312)      | 0.025 ***<br>(2.838)    | 0.020<br>(0.652)        |
| Board              | −0.011<br>(−1.441)      | −0.003<br>(−0.483)     | −0.002<br>(−0.113)        | −0.024 ***<br>(−3.100)  | −0.025 *<br>(−1.837)    |
| Indeboard          | −0.000<br>(−0.030)      | −0.000<br>(−0.687)     | −0.001<br>(−1.480)        | −0.000<br>(−1.391)      | −0.001 **<br>(−2.155)   |
| Constant           | 0.407 ***<br>(12.598)   | 0.147 ***<br>(4.388)   | −12.519 ***<br>(−134.891) | 0.517 ***<br>(14.774)   | 0.576 ***<br>(4.308)    |
| Fixed effect       | Yes                     | Yes                    | Yes                       | Yes                     | Yes                     |
| N                  | 17,365                  | 6992                   | 19,637                    | 13,052                  | 19,637                  |
| Adj.R <sup>2</sup> | 0.929                   | 0.944                  | 0.956                     | 0.935                   | 0.938                   |

Note: \*\*\*, \*\*, \* indicate significant statistical significance at 1%, 5%, and 10%, respectively.

Moreover, we measure the artificial intelligence level using patents. We add 1 to the number of applications for corporate artificial intelligence patents and take the natural logarithm (AI3). As shown in Column (2) of Table 7, AI3 still significantly inhibits carbon emissions.

##### 4.6.2. Changing the Measurement Method of Carbon Emissions

This study also takes the natural logarithm of total carbon emissions (CE2) to measure the corporate carbon emission level. The empirical outcomes are shown in Column (3) of Table 7. The coefficient of AI still presents a significant negative trend.

#### 4.6.3. Changing Sample Time Range

We further exclude samples with special time attributes to carry out robustness tests (Column (4) of Table 7). Specifically, we drop all observations covering the period from 2019 to 2021 that are affected by the COVID-19 pandemic [28,101,118]. The coefficient of AI remains significantly negative, confirming the robustness of the basic relationship between artificial intelligence and carbon emissions.

#### 4.6.4. Changing Fixed Effects

We replace industry fixed effects with enterprise fixed effects (Column (5) of Table 7). The coefficient of AI remains significantly negative, confirming the robustness of the basic relationship between artificial intelligence and carbon emissions.

### 4.7. Mechanism Analysis

#### 4.7.1. Technological Empowerment

To verify the technology empowerment mechanism, we take green technology innovation as the mediating variable. We obtain corporate green patent data from CNRDS (Chinese Research Data Services Platform), and take the logarithm of the data after adding 1 (GI) [28,119]. We then regress GI on AI (Column (1) of Table 8), finding that artificial intelligence can significantly promote green innovation.

**Table 8.** Mechanism analysis.

|         | (1)<br>GI                 | (2)<br>CE               | (3)<br>TFP             | (4)<br>CE               | (5)<br>Analyst          | (6)<br>CE               |
|---------|---------------------------|-------------------------|------------------------|-------------------------|-------------------------|-------------------------|
|         | Technological Empowerment |                         | Production Empowerment |                         | Supervision Empowerment |                         |
| AI      | 4.450 ***<br>(4.862)      | −0.0088 ***<br>(−6.378) | 0.047 ***<br>(10.456)  | −0.0087 ***<br>(−5.829) | 0.995 ***<br>(6.679)    | −0.006 ***<br>(−3.499)  |
| GI      |                           | −0.000 ***<br>(−2.625)  |                        |                         |                         |                         |
| TFP     |                           |                         |                        | −0.009 **<br>(−2.107)   |                         |                         |
| Analyst |                           |                         |                        |                         |                         | −0.001 ***<br>(−7.228)  |
| Size    | 12.202 ***<br>(15.360)    | 0.002 *<br>(1.890)      | 0.594 ***<br>(218.983) | 0.007 **<br>(2.529)     | 4.731 ***<br>(49.012)   | 0.008 ***<br>(5.179)    |
| Lev     | −2.083<br>(−1.600)        | 0.032 ***<br>(3.572)    | 0.043 **<br>(2.387)    | 0.032 ***<br>(3.588)    | −1.600 ***<br>(−2.922)  | 0.038 ***<br>(3.470)    |
| ROA     | 2.781<br>(0.562)          | −0.537 ***<br>(−18.707) | 1.106 ***<br>(18.588)  | −0.528 ***<br>(−17.983) | 69.164 ***<br>(33.800)  | −0.496 ***<br>(−13.024) |
| Cash    | 2.401<br>(0.525)          | −0.134 ***<br>(−6.133)  | −0.408 ***<br>(−9.717) | −0.161 ***<br>(−6.844)  | 2.656 *<br>(1.866)      | −0.126 ***<br>(−4.786)  |
| Growth  | −2.524 **<br>(−1.988)     | −0.020 ***<br>(−4.097)  | −0.059 ***<br>(−6.789) | −0.018 ***<br>(−3.656)  | 1.027 ***<br>(3.601)    | −0.020 ***<br>(−3.901)  |
| SOE     | 1.249 *<br>(1.929)        | 0.013 ***<br>(4.512)    | 0.014 ***<br>(2.755)   | 0.012 ***<br>(4.221)    | −1.622 ***<br>(−8.247)  | 0.015 ***<br>(4.332)    |
| AT      | 0.220<br>(0.342)          | 0.081 ***<br>(18.717)   | 1.231 ***<br>(125.781) | 0.087 ***<br>(12.691)   | −0.803 ***<br>(−3.330)  | 0.085 ***<br>(16.844)   |
| Age     | −5.153 ***<br>(−3.509)    | 0.015 ***<br>(3.589)    | 0.019 **<br>(2.368)    | 0.017 ***<br>(3.776)    | −1.509 ***<br>(−5.911)  | 0.009 *<br>(1.901)      |
| Dual    | 3.269 ***<br>(5.500)      | −0.004 *<br>(−1.915)    | 0.010 **<br>(2.110)    | −0.003<br>(−1.327)      | 0.716 ***<br>(4.574)    | −0.005 *<br>(−1.881)    |

Table 8. Cont.

|                    | (1)<br>GI                 | (2)<br>CE | (3)<br>TFP             | (4)<br>CE | (5)<br>Analyst          | (6)<br>CE |
|--------------------|---------------------------|-----------|------------------------|-----------|-------------------------|-----------|
|                    | Technological Empowerment |           | Production Empowerment |           | Supervision Empowerment |           |
| Top_1              | −3.325 *                  | 0.024 *** | 0.044 ***              | 0.033 *** | −3.645 ***              | 0.017 *   |
|                    | (−1.797)                  | (2.979)   | (2.865)                | (3.969)   | (−6.701)                | (1.752)   |
| Board              | −5.771 **                 | −0.018 ** | −0.028 *               | −0.010    | 0.950 *                 | −0.020 ** |
|                    | (−2.256)                  | (−2.570)  | (−1.916)               | (−1.339)  | (1.744)                 | (−2.433)  |
| Indeboard          | 0.281 **                  | −0.000    | −0.001**               | −0.000    | 0.072 ***               | −0.000    |
|                    | (2.490)                   | (−0.888)  | (−2.002)               | (−0.793)  | (4.099)                 | (−1.229)  |
| Constant           | −245.070 ***              | 0.447 *** | −6.141 ***             | 0.401 *** | −93.385 ***             | 0.365 *** |
|                    | (−14.952)                 | (13.776)  | (−92.022)              | (9.671)   | (−39.442)               | (9.128)   |
| Fixed effect       | Yes                       | Yes       | Yes                    | Yes       | Yes                     | Yes       |
| N                  | 19,604                    | 19,604    | 17,315                 | 17,315    | 14,142                  | 14,142    |
| Adj.R <sup>2</sup> | 0.151                     | 0.931     | 0.919                  | 0.935     | 0.380                   | 0.929     |

Note: \*\*\*, \*\*, \* indicate significant statistical significance at 1%, 5%, and 10%, respectively.

We then incorporate GI into the baseline regression (Column (2) of Table 8). The results indicate a reduction in the statistical significance of the AI coefficient (from  $-6.599$  to  $-6.378$ ), indicating that green innovation significantly attenuates the influence of artificial intelligence on carbon emissions. Additionally, the absolute value of the AI coefficient decreases from  $0.009$  to  $0.0088$ . Consequently, this provides more robust empirical support for our mechanism analysis, confirming that GI serves as a mediator in the relationship between AI and CE.

#### 4.7.2. Production Empowerment

To verify the production empowerment mechanism, we use corporate total factor productivity as the mediating variable. We construct the corporate total factor productivity indicator (TFP) using the LP semi-parametric method [120,121]. Artificial intelligence significantly improves TFP (Column (2) of Table 8), indicating that the production empowerment mechanism is valid.

We then incorporate TFP into the baseline regression (Column (4) of Table 8). The results indicate a reduction in the statistical significance of the AI coefficient (from  $-6.599$  to  $-5.829$ ), indicating that TFP significantly attenuates the influence of artificial intelligence on carbon emissions. Additionally, the absolute value of the AI coefficient decreases from  $0.009$  to  $0.0087$ . Consequently, this provides more robust empirical support for our mechanism analysis, confirming that TFP serves as a mediator in the relationship between AI and CE.

#### 4.7.3. Supervision Empowerment

To verify the supervision empowerment mechanism, we take analyst attention as the mediating variable [120,122]. We obtain corporate analyst attention data (Analyst) from CSMAR and regress it on AI. Artificial intelligence significantly increases the analyst attention of manufacturing enterprises (Column (3) of Table 8), which proves that the supervision empowerment mechanism is established.

We then incorporate Analyst into the baseline regression (Column (6) of Table 8). The results indicate a reduction in the statistical significance of the AI coefficient (from  $-6.599$  to  $-3.499$ ), indicating that Analyst significantly attenuates the influence of artificial intelligence on carbon emissions. Additionally, the absolute value of the AI coefficient decreases from  $0.009$  to  $0.006$ . Consequently, this provides more robust empirical support for our mechanism analysis, confirming that Analyst serves as a mediator in the relationship between AI and CE.

#### 4.8. Heterogeneity Analysis

##### 4.8.1. Enterprise Property

The special governance structure and institutional positioning of state-owned enterprises (SOEs) help them achieve more prominent carbon reduction gains from artificial intelligence. Such advantages take effect across three core channels: technological empowerment, production empowerment and supervision empowerment.

SOEs serve as core executors of national low-carbon and digital development strategies [123,124]. Their institutional arrangements link operational planning to national strategic targets, including carbon peaking and carbon neutrality. They also maintain robust technology absorption capacity and sustained long-term research and development investment [125,126]. These inherent strengths lay a solid foundation for green technological innovation supported by artificial intelligence. Non-SOEs usually face tight short-term performance demands. By contrast, SOEs can carry out long-cycle, capital-intensive low-carbon research projects powered by artificial intelligence without constraints from short-term profit goals. This feature guarantees steady progress and tangible outputs of green innovation activities.

From the perspective of production and operation, SOEs generally own complete organizational frameworks, standardized process management and large-scale production bases [127–129]. These conditions help translate AI-driven efficiency growth into tangible emission reduction results. The deployment of artificial intelligence in process optimization, energy scheduling, equipment management and other production segments demands cross-departmental coordination and unified resource allocation [28]. SOEs possess strong internal execution and resource integration capabilities. They lower organizational frictions during intelligent upgrading, roll out artificial intelligence systems across full production chains at a faster speed, and fully capture energy-saving and emission-reduction gains from improved total factor productivity. The operational scale of SOEs further magnifies such benefits. Larger production ranges covered by artificial intelligence empowerment correspond to more obvious marginal carbon reduction brought by efficiency optimization.

For external supervision, SOEs are subject to dual restraints from government environmental evaluation and public social responsibility requirements [127–129]. They also shoulder the mission of setting green transformation benchmarks for the whole industry. These two layers of pressure push SOEs to actively adopt artificial intelligence and construct transparent, standardized corporate carbon emission management systems. On one side, comprehensive government evaluation for SOEs covers both economic returns and environmental governance performance. This institutional arrangement encourages SOEs to deploy artificial intelligence for full-process carbon monitoring and refined carbon management to strictly lower carbon emission intensity. On the other side, the public nature of SOEs draws greater attention from capital market analysts and the general public [127–129]. Artificial intelligence adoption improves the transparency of corporate carbon information and reinforces the oversight function of external analysts, forming stricter restraints on corporate carbon emission practices.

This study constructs the interaction term AI\_SOE by combining AI and the SOE attribute to verify the moderating effect of enterprise property. The constructed variable is incorporated into the regression model, and the corresponding results are presented in Column (1) of Table 9. The coefficient of AI\_SOE is significantly negative, confirming that enterprise ownership plays a prominent moderating role in the correlation between artificial intelligence and carbon emissions.

**Table 9.** Heterogeneity analysis: enterprise property.

|                    | (1)                     | (2)                     | (3)                    |
|--------------------|-------------------------|-------------------------|------------------------|
|                    | Interaction Term        | SOEs                    | Non-SOEs               |
|                    | CE                      | CE                      | CE                     |
| AI                 | −0.007 ***<br>(−4.352)  | −0.011 ***<br>(−3.534)  | −0.003<br>(−1.269)     |
| AI_SOE             | −0.013 ***<br>(−4.528)  |                         |                        |
| Size               | 0.002 *<br>(1.666)      | 0.003<br>(1.251)        | −0.001<br>(−0.228)     |
| Lev                | 0.031 ***<br>(3.509)    | 0.008<br>(0.460)        | 0.055 ***<br>(2.937)   |
| ROA                | −0.537 ***<br>(−18.723) | −0.629 ***<br>(−11.926) | −0.423 ***<br>(−9.045) |
| Cash               | −0.135 ***<br>(−6.176)  | −0.180 ***<br>(−4.084)  | −0.078 **<br>(−2.398)  |
| Growth             | −0.020 ***<br>(−4.100)  | −0.005<br>(−0.518)      | −0.014 **<br>(−2.078)  |
| SOE                | 0.015 ***<br>(5.003)    |                         |                        |
| AT                 | 0.081 ***<br>(18.762)   | 0.072 ***<br>(8.805)    | 0.039 **<br>(2.522)    |
| Age                | 0.015 ***<br>(3.701)    | 0.015<br>(1.592)        | −0.005<br>(−0.121)     |
| Dual               | −0.005 **<br>(−2.044)   | 0.001<br>(0.145)        | −0.001<br>(−0.171)     |
| Top_1              | 0.024 ***<br>(2.969)    | 0.041 ***<br>(2.647)    | 0.014<br>(0.383)       |
| Board              | −0.018 **<br>(−2.571)   | 0.016<br>(1.216)        | −0.037 **<br>(−2.438)  |
| Indeboard          | −0.000<br>(−1.026)      | 0.000<br>(0.669)        | −0.001 ***<br>(−2.861) |
| Constant           | 0.454 ***<br>(14.501)   | 0.484 ***<br>(8.383)    | 0.659 ***<br>(4.056)   |
| Fixed effect       | Yes                     | Yes                     | Yes                    |
| N                  | 19,637                  | 5032                    | 14,605                 |
| Adj.R <sup>2</sup> | 0.931                   | 0.950                   | 0.935                  |

Note: \*\*\*, \*\*, \* indicate significant statistical significance at 1%, 5%, and 10%, respectively. The difference in the AI coefficient in group regression is the additional economic effect generated.

In addition, group regression tests are adopted to further identify the additional economic effects generated by corporate property types. Samples are classified into SOEs and non-SOEs groups. Results from this subgroup analysis appear in Columns (2)–(3) of Table 9, showing that the AI coefficient is significantly negative and the absolute value is larger in the SOEs subgroup. This indicates that the inhibitory effect of AI on carbon emissions is more pronounced in SOEs.

#### 4.8.2. Nature of Enterprise Pollution

Due to their high energy consumption and high emission production characteristics [130], polluting enterprises may have greater potential to release emission reduction effects when applying artificial intelligence technology.

In terms of green technology development, polluting enterprises have a more urgent demand for environmental protection technologies [130], and clean production process innovations driven by artificial intelligence are more likely to be rapidly applied in these enterprises. At the level of production efficiency improvement, the production processes of traditional polluting enterprises often have a large number of redundant links. The

intervention of artificial intelligence can effectively identify and eliminate these inefficient nodes, thereby reducing energy waste while increasing production capacity.

External supervision pressure is also an important factor. Polluting enterprises usually face stricter environmental regulations and public attention [131,132]. This urges them to take the initiative to adopt artificial intelligence to build a transparent environmental information disclosure system for meeting regulatory requirements and social responsibilities. Driven by multiple mechanisms, the emission reduction effect of artificial intelligence technology in polluting enterprises is more prominent.

To verify the moderating effect of the nature of enterprise pollution, we construct a dummy variable (Pollu) for polluting enterprises. Specifically, with reference to the “Guidelines for Environmental Information Disclosure of Listed Companies” issued by the Ministry of Environmental Protection of China, we regard industries such as thermal power, iron and steel, cement, electrolytic aluminum, coal, metallurgy, chemical industry, petrochemical industry, building materials, papermaking, brewing, pharmaceutical, fermentation, textile, tanning and mining as polluting industries [130]. We construct the interaction term AI\_Pollu by combining AI and Pollu, including it in the regression model (Column (1) of Table 10). We find that the coefficient of AI\_Pollu is significantly negative, indicating that the nature of enterprise pollution has a moderating effect on the relationship between artificial intelligence and carbon emissions.

**Table 10.** Heterogeneity analysis: nature of enterprise pollution.

|                    | (1)                    | (2)                     | (3)                       |
|--------------------|------------------------|-------------------------|---------------------------|
|                    | Interaction Term       | Polluting Enterprises   | Non-Polluting Enterprises |
|                    | CE                     | CE                      | CE                        |
| AI                 | −0.001 ***<br>(−5.916) | −0.044 ***<br>(−3.660)  | 0.000<br>(0.283)          |
| AI_Pollu           | −0.009 *<br>(−1.869)   |                         |                           |
| Size               | 0.001<br>(0.525)       | 0.009 **<br>(2.488)     | −0.004 *<br>(−1.886)      |
| Lev                | 0.045 ***<br>(4.165)   | 0.061 **<br>(2.261)     | 0.024 ***<br>(3.498)      |
| ROA                | −0.403 ***<br>(−9.142) | −1.546 ***<br>(−14.798) | −0.117 ***<br>(−6.606)    |
| Cash               | −0.144 ***<br>(−4.562) | −0.263 ***<br>(−4.433)  | −0.048 ***<br>(−3.595)    |
| Growth             | −0.000 *<br>(−1.756)   | −0.039 **<br>(−2.546)   | −0.001<br>(−0.241)        |
| SOE                | 0.015 ***<br>(5.175)   | 0.016 **<br>(2.022)     | 0.007 ***<br>(3.177)      |
| AT                 | 0.063 ***<br>(14.572)  | 0.163 ***<br>(17.432)   | 0.010<br>(1.625)          |
| Age                | 0.022 ***<br>(3.194)   | 0.044 ***<br>(3.307)    | 0.016<br>(1.193)          |
| Dual               | −0.007 ***<br>(−2.708) | −0.022 ***<br>(−2.883)  | −0.002<br>(−1.434)        |
| Top_1              | 0.029 ***<br>(3.405)   | 0.053 *<br>(1.953)      | −0.009<br>(−0.918)        |
| Board              | −0.023 ***<br>(−2.758) | −0.048 **<br>(−2.007)   | −0.000<br>(−0.039)        |
| Indeboard          | −0.000<br>(−1.098)     | −0.001<br>(−1.530)      | −0.000<br>(−0.332)        |
| Constant           | 0.505 ***<br>(15.673)  | 1.206 ***<br>(12.035)   | 0.248 ***<br>(4.916)      |
| Fixed effect       | Yes                    | Yes                     | Yes                       |
| N                  | 19,637                 | 5254                    | 14,383                    |
| Adj.R <sup>2</sup> | 0.908                  | 0.841                   | 0.830                     |

Note: \*\*\*, \*\*, \* indicate significant statistical significance at 1%, 5%, and 10%, respectively. The difference in the AI coefficient in group regression is the additional economic effect generated.

In addition, we adopt group regression tests to further identify the additional economic effects generated by the nature of enterprise pollution. Samples are classified into polluting and non-polluting groups. The coefficient of AI is significantly negative, and the absolute value is larger in the polluting subgroup (Columns (2)–(3) of Table 10). This indicates that the inhibitory effect of AI on carbon emissions is more pronounced among polluting enterprises.

#### 4.8.3. Corporate Financing Constraints

Enterprises with stronger financing constraints may show more significant effects in using artificial intelligence to curb carbon emissions. These enterprises have limited ability to obtain funds [133], making it difficult to implement traditional high-cost emission reduction technologies. However, artificial intelligence can improve energy efficiency and control emissions at a relatively low cost through data-driven and algorithm optimization [134,135].

In terms of green technology development, financing constraints force enterprises to pay more attention to marginal benefits of technological investment. Artificial intelligence technology can accurately identify the links with the greatest emission reduction potential and carry out targeted innovation, thus maximizing the output of green technology with limited resources.

In terms of production efficiency improvement, capital shortages often lead to more serious resource misallocation and process redundancy in such enterprises [136,137]. The intervention of artificial intelligence can systematically optimize production parameters and supply chain management. The emission reduction effect brought by efficiency improvement is more prominent in enterprises with poor basic conditions.

External supervision pressure also plays a reinforcing role. Enterprises with financing constraints usually face stricter credit review and investor attention [138]. This urges them to take the initiative to adopt artificial intelligence technology to build a transparent environmental performance management system so as to improve financing conditions [101,139]. Driven by multiple mechanisms, the emission reduction efficiency of artificial intelligence technology in enterprises with financing constraints is fully released.

To verify the moderating effect of financing constraints, we obtain the financing constraints indicator (FC index) from CSMAR, constructing the dummy variable *Finan* [136]. Specifically, if the financing constraint of an enterprise is below the sample median, *Finan* is assigned a value of 1, otherwise 0. We combine AI and *Finan* to construct the interaction term *AI\_Finan* and include it in the regression model (Column (1) of Table 11). We find that the coefficient of *AI\_Finan* is significantly negative, indicating that financing constraints have a moderating effect on the relationship between artificial intelligence and carbon emissions.

**Table 11.** Heterogeneity analysis: financing constraints.

|          | (1)                    | (2)                        | (3)                       |
|----------|------------------------|----------------------------|---------------------------|
|          | Interaction Term       | High Financing Constraints | Low Financing Constraints |
|          | CE                     | CE                         | CE                        |
| AI       | −0.006 ***<br>(−3.544) | −0.014 ***<br>(−7.368)     | −0.004 *<br>(−1.766)      |
| AI_Finan | −0.007 ***<br>(−2.885) |                            |                           |
| Finan    | 0.033 ***<br>(3.320)   |                            |                           |
| Size     | 0.009 ***<br>(3.929)   | 0.012 ***<br>(4.297)       | 0.001<br>(0.364)          |

Table 11. Cont.

|                    | (1)                     | (2)                        | (3)                       |
|--------------------|-------------------------|----------------------------|---------------------------|
|                    | Interaction Term        | High Financing Constraints | Low Financing Constraints |
|                    | CE                      | CE                         | CE                        |
| Lev                | 0.044 ***<br>(4.589)    | −0.007<br>(−0.524)         | 0.054 ***<br>(4.276)      |
| ROA                | −0.559 ***<br>(−19.252) | −0.642 ***<br>(−15.464)    | −0.484 ***<br>(−12.460)   |
| Cash               | −0.124 ***<br>(−5.647)  | −0.133 ***<br>(−4.595)     | −0.150 ***<br>(−4.710)    |
| Growth             | −0.019 ***<br>(−3.985)  | −0.034 ***<br>(−5.180)     | −0.008<br>(−1.199)        |
| SOE                | 0.013 ***<br>(4.561)    | 0.010 **<br>(2.400)        | 0.013 ***<br>(3.285)      |
| AT                 | 0.081 ***<br>(18.554)   | 0.113 ***<br>(16.459)      | 0.069 ***<br>(12.477)     |
| Age                | 0.016 ***<br>(3.773)    | 0.018 ***<br>(3.265)       | 0.010 *<br>(1.733)        |
| Dual               | −0.005 **<br>(−2.096)   | −0.001<br>(−0.448)         | −0.008 **<br>(−2.254)     |
| Top_1              | 0.023 ***<br>(2.799)    | 0.023 **<br>(2.063)        | 0.019<br>(1.574)          |
| Board              | −0.019 ***<br>(−2.682)  | −0.048 ***<br>(−4.786)     | 0.008<br>(0.763)          |
| Indeboard          | −0.000<br>(−1.095)      | −0.001 ***<br>(−2.637)     | 0.000<br>(0.633)          |
| Constant           | 0.292 ***<br>(5.291)    | 0.274 ***<br>(4.114)       | 0.464 ***<br>(10.632)     |
| Fixed effect       | Yes                     | Yes                        | Yes                       |
| N                  | 19,625                  | 9799                       | 9826                      |
| Adj.R <sup>2</sup> | 0.931                   | 0.925                      | 0.937                     |

Note: \*\*\*, \*\*, \* indicate significant statistical significance at 1%, 5%, and 10%, respectively. The difference in the AI coefficient in group regression is the additional economic effect generated.

In addition, we adopt group regression tests to verify the additional economic effects caused by financing constraints (Columns (2)–(3) of Table 10). Samples are classified into high financing constraints and low financing constraints groups, showing that the AI coefficient is significantly negative and the absolute value is larger in the high financing constraints subgroup. This indicates that the inhibitory effect of AI on carbon emissions is more pronounced among high financing constraint enterprises.

## 5. Conclusions, Discussion, Implications, and Limitations

### 5.1. Conclusions

We take Chinese listed manufacturing enterprises as samples, finding that artificial intelligence can significantly inhibit carbon emissions. Furthermore, we find that artificial intelligence reduces carbon emissions mainly through technology empowerment, production empowerment and supervision empowerment. Specifically, artificial intelligence promotes green innovation, total factor productivity and analyst attention. Finally, we focus on the synergistic effects brought about by the nature of the enterprise and financial resource conditions. We find that the inhibitory effect of artificial intelligence is more significant in SOEs, polluting enterprises and enterprises with stronger financing constraints.

### 5.2. Discussion

Modern society adheres to the people-centered development philosophy [140]. Improving human well-being serves as the fundamental goal of development [128]. Eco-

logical and environmental protection forms an essential foundation for public well-being [130,141–144]. Carbon emission governance acts as a core guarantee for sustainable social development. This paper investigates the correlation between artificial intelligence and carbon emissions of manufacturing enterprises, with special attention paid to its influencing channels and heterogeneous impacts. This research maintains close connections with Zhou and Shao [145], as well as He and Chen [146]. All three papers discuss the carbon reduction benefits of digital technologies at the micro enterprise level and supply empirical evidence based on China's context. We expand this research stream by centering on artificial intelligence, a core frontier technology for digital transformation. We systematically sort out the carbon mitigation logic of artificial intelligence under the TOE framework.

Zhou and Shao [145] analyzed how generalized digital transformation shapes carbon emissions and regarded manufacturing servitization as the core mediating path. Our paper narrows the research scope to artificial intelligence application. Artificial intelligence is closely related to digital transformation yet carries unique technical characteristics. Conventional digital transformation includes informatization, networking and general digital process reconstruction. Artificial intelligence represents advanced digital intelligence with autonomous learning, intelligent decision-making and iterative optimization capabilities. It delivers more targeted empowerment for corporate innovation, production operation and environmental governance. Our paper identifies three independent transmission paths, including technological empowerment, production empowerment and supervision empowerment, which differ from the servitization channel proposed by Zhou and Shao [145]. Our multi-dimensional internal and external mechanisms jointly verify the carbon suppression effect of artificial intelligence and advance theoretical cognition of intelligent technology and corporate carbon performance. For heterogeneity tests, Zhou and Shao [145] divided samples according to corporate technical intensity, life cycle and geographic location. Our paper adds two new grouping dimensions, namely corporate pollution intensity and resource endowment. The results show that artificial intelligence generates stronger carbon reduction outcomes in polluting enterprises and enterprises with insufficient resource reserves. This finding expands the scope of heterogeneous analysis and delivers differentiated practical suggestions for enterprises with varied environmental characteristics and resource conditions.

He and Chen [146] split the carbon emission impact of digital transformation into two parts. The first part is the direct carbon growth effect driven by rising power consumption. The second part refers to indirect carbon reduction brought by productivity growth and energy conservation. He and Chen [146] explained influence paths from a purely empirical perspective. Our paper deepens theoretical interpretation of digital technology and carbon emissions via the TOE theoretical framework. Our paper incorporates three empowerment mechanisms into the TOE framework to build a complete analytical logic. Our study matches the three empowerment paths with the three core contextual layers of the TOE framework one by one. We expand the technological context by connecting artificial intelligence with corporate green innovation, illustrating how intelligent technologies push forward low-carbon technical upgrades as a technical factor. We enrich the organizational context by linking artificial intelligence to total factor productivity, demonstrating how artificial intelligence optimizes internal production arrangements. We also extend the environmental context by introducing strengthened analyst supervision and reveal the external governance function of artificial intelligence in corporate carbon emission management. Analysis built on this framework clarifies the theoretical scope of each mechanism, constructing a unified analytical standard for research on intelligent technology carbon reduction. Such processing lifts the theoretical depth of related literature.

Overall, this paper expands existing literature about digital transformation and corporate carbon emissions from three dimensions, including research content, mechanism identification and theoretical construction. It separates artificial intelligence from generalized digital transformation and verifies multi-dimensional carbon reduction empowerment effects in manufacturing sectors. This work deepens micro-level research on digital carbon mitigation from the technical perspective. Mechanism analysis based on the TOE framework offers systematic theoretical explanations for the carbon emission influence of artificial intelligence. It enriches relevant theoretical studies and provides policy references for advancing intelligent low-carbon upgrading among manufacturing enterprises.

### *5.3. Theoretical Implications*

This research expands and supplements the TOE framework through an analysis of the multi-dimensional empowerment effect of artificial intelligence on carbon emission reduction. This paper verifies the applicability of the TOE framework to carbon governance driven by artificial intelligence within the manufacturing industry. It also broadens the connotation of the framework by sorting out the operating mechanisms of three core dimensions during corporate decarbonization.

Specifically, this study supplements the three core contextual layers of the TOE framework from the perspective of carbon emission management. It expands the technological context by establishing its connection with corporate green innovation. This logical link supports the transformation of artificial intelligence investment into tangible low-carbon technological outputs.

The research enriches the organizational context by connecting it with the growth of total factor productivity. It highlights how artificial intelligence optimizes internal production systems and operational efficiency to lower corporate carbon emission intensity.

Furthermore, this paper extends the environmental context by anchoring it to strengthened analyst supervision. It identifies the synergistic interaction between external information governance factors and the carbon reduction benefits generated by artificial intelligence.

The clear elaboration of multi-dimensional mechanisms improves the theoretical value of the TOE framework for studies focusing on corporate low-carbon transition and digital decarbonization.

### *5.4. Practical Implications*

This study provides an important path for the realization of sustainable development goals and thus has important practical implications for promoting the green transformation of manufacturing industry. First, the government should focus on supporting high-pollution industries to establish demonstration projects for artificial intelligence application, accelerating the promotion of green production technologies through special fund support and tax incentives. Second, SOEs should take the lead in incorporating the emission reduction effect of artificial intelligence into the performance appraisal system, driving the coordinated carbon reduction in the industrial chain. Finally, financial regulatory authorities need to improve green credit policies, providing financing convenience for enterprises adopting artificial intelligence emission reduction technologies.

### *5.5. Limitations and Future Research*

This study measures carbon emission intensity as the ratio of an enterprise's total carbon emissions to its operating revenue. Carbon emission data are retrieved from the CSMAR database. This authoritative dataset is widely adopted in micro-level studies on corporate carbon emissions. It contains complete carbon emission records of listed enterprises, and this measurement method has been extensively applied in existing relevant

literature with strong universality and comparability. However, several points can be supplemented regarding the measurement of this indicator. First, product prices may generate minor interference. Intensity indicators using operating revenue as the denominator are susceptible to fluctuations in corporate product prices. Second, inflation brings potential bias. Macroeconomic inflation raises nominal corporate operating revenue and distorts vertical comparisons of carbon emission intensity across years. Third, indicators based on physical output may deliver better production-side comparability. The current value-based intensity measurement cannot directly reflect carbon efficiency during production activities. In addition, some unobservable inherent traits of each enterprise may not be captured in the model. This drawback exists in most micro empirical research focusing on corporate operational behaviors.

The tests conducted above cannot be expanded across the full sample due to limited disclosure and accessibility of segmented physical output data for listed enterprises. As disclosure rules for corporate environmental and operational information improve in the future, cross-verification through multiple measurement standards can further strengthen the robustness of carbon emission intensity measurement. Meanwhile, micro-level corporate data will become increasingly abundant in the future. Subsequent research can integrate more detailed enterprise-specific features into the analysis framework. This approach can better reduce bias caused by omitted variables and raise the precision of causal identification.

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## Appendix A

**Table A1.** Artificial intelligence keywords.

| Artificial Intelligence | Knowledge Representation   | Edge Computing      | Enhance Intelligence        | Biometrics              | Support Vector Machine | Big Data Platform     |
|-------------------------|----------------------------|---------------------|-----------------------------|-------------------------|------------------------|-----------------------|
| AI product              | Pattern recognition        | Cloud computing     | Big data operation          | Speech recognition      | Smart chip             | Voice interaction     |
| AI chip                 | Internet of Things         | Deep neural network | Neural network              | Intelligent supervision | Wearable products      | Business intelligence |
| Machine translation     | Human-machine dialogue     | Deep learning       | Speech synthesis            | Robo-advisor            | Intelligent computing  | Big data marketing    |
| Machine learning        | Human-computer interaction | Feature recognition | Human-machine collaboration | Intelligent voice       | Feature extraction     | Smart healthcare      |

Table A1. Cont.

|                    |                              |                          |                              |                             |                       |                                      |
|--------------------|------------------------------|--------------------------|------------------------------|-----------------------------|-----------------------|--------------------------------------|
| Computer vision    | Data mining                  | Intelligent insurance    | Intelligent agriculture      | Voiceprint recognition      | Smart finance         | Big data management                  |
| Image recognition  | Smart banking                | Intelligent retail       | Smart speaker                | Face recognition            | Big data risk control | Intelligent environmental protection |
| Knowledge graph    | Intelligent customer service | Robot process automation | Convolutional neural network | Natural language processing | Agent                 | Smart education                      |
| Virtual reality    | Intelligent transportation   | Q&A system               | Big data processing          | Intelligent search          | Augmented reality     | Autonomous driving                   |
| Smart home         | Reinforcement learning       | Distributed computing    | Big data analytics           | Smart government            | Self-driving          | Recurrent neural network             |
| Smart elderly care | Long short-term memory       | Smart sensor             |                              |                             |                       |                                      |

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