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The Impact of Artificial Intelligence on the Sustainable Development Performance of Chinese Manufacturing Enterprises

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Abstract

As a major driving force in the current technological revolution, artificial intelligence (AI) has significantly accelerated the intelligence, automation, and informatization of enterprises, thereby inevitably influencing the sustainable development performance (SDP) of manufacturing enterprises. This study takes the "Next-Generation AI Innovation Pilot Zone" policy as a case study and utilizes a multi-period difference-in-differences (DID) model and machine learning techniques to investigate the impact of AI on the SDP of Chinese manufacturing enterprises. The findings indicate that AI contributes to improving the SDP of manufacturing firms. The mechanism analysis reveals that AI enhances SDP via a green innovation effect, cost-saving effect, and digital transformation effect. The moderation analysis further shows that the CEO duality inhibits the positive impact of AI on SDP. The heterogeneity results based on the GRF model indicate that the positive relationship between AI and SDP is pronounced in state-owned enterprises and heavily polluting firms. This study not only enriches the literature on the micro-level environmental effects of AI but also provides valuable insights for governments and businesses seeking to improve SDP.

Keywords: artificial intelligence; sustainable development performance; generalized random forest; quasi-natural experiment

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1. Introduction

The rapid development of the global economy and society has gradually led leaders and business managers around the world to recognize that economic growth alone does not necessarily equate to genuine social well-being. As a result, the pursuit of environmental and social sustainability within organizations has become a focal point for academic inquiry. In 2015, the United Nations introduced the 2030 Agenda for Sustainable Development, which underscores the integration of sustainability principles across all stages of production and consumption, aiming to foster harmony between humanity and the planet and to ensure the enduring prosperity of human civilization. China has also identified sustainable development as a vital pathway toward socialist modernization. In 2020, the Chinese government set forth its "dual carbon" targets, calling on enterprises to adopt energy-efficient and carbon-reducing production methods to mitigate their emissions. In recent years, China's growing commitment to ecological civilization has rendered the realization of these dual carbon targets a profound and widespread transformation across multiple industries. As a sector characterized by extensive value chains, high interconnectivity, and significant externalities, manufacturing plays a pivotal role in the national economy [1]. Consequently,

the generation of environmental and social value has increasingly become a key indicator of sustainable development performance (SDP) among manufacturing firms. Artificial intelligence (AI), as a transformative technology, has emerged as a major driver of technological revolutions and industrial upgrading. Countries such as the United States, European Union member states, and the United Kingdom have incorporated AI into their national strategies. Similarly, The Chinese government has prioritized AI in advancing its national development goals. Since 2019, China has established 18 next-generation AI innovation pilot zones (AIPZ), including Beijing, Shanghai, Tianjin, and Shenzhen—thereby creating a supportive ecosystem encompassing core technologies, infrastructure, and application scenarios. In its 2024 Government Work Report, the Chinese government reaffirmed its commitment to deepening AI and big data research and applications, promoting the launch of initiatives under the "AI+" framework. AI-driven innovation is reshaping industries at an extraordinary scale. In particular, it is transforming key production factors, technological systems, institutional arrangements, and value frameworks. In the manufacturing sector, the integration of AI enables real-time monitoring of pollution emissions, optimization of clean production processes, and green enhancements across industrial operations [2]. Therefore, promoting the intelligent upgrading of manufacturing firms constitutes a viable pathway toward China's green transformation [3].

In academia, growing attention has been directed toward new models of sustainable development in the digital era. Prior studies have affirmed the positive impact of digital culture, digital orientation, and digital technologies on corporate sustainability [4–6]. As a core technological resource, AI also plays an irreplaceable role in achieving SDP. Nevertheless, this topic has so far received limited scholarly attention. The existing literature often uses the deployment of industrial robots as a proxy for AI adoption. However, industrial robots account for only a narrow segment of AI applications and fail to capture the broader and more dynamic roles that AI plays in corporate production and management. This raises several key research questions: Can AI enhance firms' SDP? Through which mechanisms does AI influence firms' sustainability performance? What empirical strategies can accurately estimate AI's impact on SDP while addressing potential endogeneity concerns? These questions form the core of this study. To mitigate bias stemming from proxy variable selection, this study exploits the 2019 establishment of China's AIPZ as a quasi-natural experiment. A multi-period difference-in-differences (DID) model is used to estimate the effect of AI on firms' SDP. While the traditional DID approach is effective for estimating average treatment effects, it is relatively limited in capturing treatment effect heterogeneity. Recent theoretical developments have shown that machine learning methods can significantly improve the estimation of heterogeneous treatment effects [7–9]. Building upon the DID framework, this study further employs the generalized random forest (GRF) model to investigate the impact of AI policy on SDP and to uncover its underlying mechanisms.

This study makes three primary contributions. First, it integrates AI and SDP into a unified analytical framework, enriching the literature on the environmental impacts of AI at the firm level. It expands existing research on the determinants of SDP and identifies effective mechanisms through which AI can enhance firms' sustainability outcomes. Second, it investigates the underlying mechanisms linking AI to SDP through three distinct channels: green innovation, cost saving, and digital transformation. Additionally, it examines the moderating role of CEO duality. These analyses deepen the understanding of how intelligent upgrading contributes to firms' green transformation, which also offers valuable policy implications for promoting AI-driven green development, particularly in energy-intensive sectors across developing countries. Third, this study introduces the GRF model to achieve causal identification and inference. Compared to with traditional econometric approaches, GRF improves the accuracy of high-dimensional regressions and

reduces functional form misspecification. Moreover, GRF enables the estimation of treatment effects at the individual level, thereby overcoming the limitations of group-level and interaction-based regression models. This methodological innovation broadens the toolkit for policy evaluation and provides policymakers with robust and granular evidence in the context of complex economic environments and rapidly evolving industrial dynamics.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature. Section 3 presents the research hypothesis. Section 4 outlines the research design. Section 5 reports the empirical results and discusses the results. Section 6 concludes the paper and offers policy recommendations.

2. Literature Review

2.1. Research on SDP

With the ongoing advancement of the sustainable development agenda, academic interest in the concept and evaluation of SDP has steadily increased. Existing studies can be broadly categorized into three areas: its conceptual definition, measurement methodologies, and influencing factors. These studies provide important theoretical foundations for the selection and construction of proxy indicators for SDP in this paper. Harris (2003) defined sustainable development as an economic state in which the environmental needs of the present generation and businesses are met without compromising the ecological capacity to support future generations [10]. Similarly, Bansal (2005) [11], conceptualized corporate sustainability as the ability of firms to address short-term economic, environmental, and social needs while safeguarding long-term benefits in these dimensions. Under the guidance of sustainable development principles, firms are expected to pursue not only economic growth, but also the balanced integration of economic, environmental, and social objectives. Notably, economic gains should not be achieved at the expense of ecological or social well-being [12]. Against this backdrop, SDP can be viewed as a multidimensional indicator reflecting a firm's effectiveness in aligning its operations with sustainability goals. In terms of performance dimensions, Krajnc and Glavic (2005) proposed that SDP consists of economic, environmental, and social responsibility dimensions [13]. Building on this framework, Xie and Zhu (2021) further disaggregated SDP into financial performance and environmental–social responsibility performance. The former captures the internal, operational sustainability of a firm, while the latter reflects its external engagement in broader environmental and social domains [14].

Growing scholarly interest has been directed toward identifying the factors that influence SDP, with research exploring leadership attributes, corporate innovation, environmental ethics, and external environmental conditions. From the perspective of leadership and corporate governance, Aksoy et al. (2020) investigated how ownership structure, board diversity, and firm-specific characteristics affect SDP in the Turkish context, drawing on stakeholder and agency theories. Their findings indicate that foreign and institutional ownership significantly promote SDP, while larger board size and a higher proportion of independent directors are also positively associated with it [15]. In terms of environmental ethics and behavior, Aftab et al. (2022) found that strong environmental ethics significantly enhance SDP in Pakistan firms, with environmental leadership and strategy serving as significant moderating variables [16]. Regarding corporate innovation, Fernando et al. (2019) argued that environmental innovation improves SDP, with service innovation capability acting as a mediator mechanism [17]. Drawing on the resource-based view and Schumpeterian innovation theory, Koliby et al. (2022) demonstrated that innovation in small-and medium-sized manufacturing enterprises enhances SDP by linking entrepreneurial capacity with sustainability outcomes [18]. Furthermore, external environmental factors have also been shown to affect SDP. For instance, climate change, economic policy uncertainty, and

political instability tend to exert negative influences [19]. More recently, with the rise of the digital economy, scholars have increasingly examined the role of digital technologies in shaping firms' sustainability outcomes. Studies have consistently reported positive effects of digital transformation on SDP [6,20]. As a core technology within the digital economy, AI holds great potential in this regard. However, whether AI can serve as a critical driver of firms' SDP remains an open empirical question, warranting further investigation.

2.2. Research on AI

There is limited literature directly examining the relationship between AI and firms' SDP. Existing studies primarily investigate the environmental implications of AI, including its effects on energy efficiency, emissions reduction, green development, and green innovation, thus offering valuable insights.

In terms of energy efficiency and emissions reduction, Li and Tian (2022) demonstrated that industrial robots enable real-time monitoring of energy use and emissions during production, thereby helping mitigate excessive emissions [21]. Duan et al. (2023) found that industrial robots facilitate clean production and enhance total factor productivity [22]. AI contributes to emissions reduction by improving production efficiency, lowering labor costs, and fostering green innovation [23]. As an advanced technology, AI enhances production automation and operational efficiency, thereby promoting green development. Lin and Xu (2024) highlighted how industrial robots enhance regional green ecological efficiency through technological advancement, energy optimization, and industrial agglomeration [24]. Zhao et al. (2024) found that AI fosters urban land green development through technological innovation, labor substitution, and emission reduction investment [25]. AI technologies, including industrial robots, play a significant role in driving green innovation. Yang et al. (2022) argued that intelligent technologies optimize production processes by reducing operational risks and costs, thereby unlocking firms' green innovation potential [26]. Nie et al. (2022) emphasized that industrial robots strengthen human capital and improve internal governance, thereby facilitating green innovation outcomes [27]. However, several studies suggest a nonlinear relationship between AI adoption and green innovation. Chen et al. (2024) revealed that while AI promotes green innovation, its effects follow a marginally increasing nonlinear pattern [28].

According to the resource-based view [29], a firm's growth, core competitiveness, and sustainable development are grounded in its resource base. As a valuable, rare, inimitable, and non-substitutable technology, AI can enhance a firm's environmental responsiveness, improve resource allocation, and reduce negative environmental externalities [30]. Additionally, AI helps bridge informational silos, support data-driven decision making, and accelerate product iterations, thereby aligning economic objectives with environmental goals and advancing corporate sustainability [31]. While some studies have examined the role of digital technologies in corporate sustainability; much of the existing research has concentrated on specific technologies—such as big data in sustaining competitive advantage and blockchain in fostering corporate sustainability [32,33]. However, as a broad and integrative technological domain, the impact of AI on firms' SDP remains underexplored.

2.3. Research on Machine Learning in Causal Inference

Traditional econometric approaches often struggle to adequately address selection bias arising from confounding variables in causal inference. Machine learning offers a robust alternative for mitigating selection bias. Within the potential outcomes framework, causal inference techniques can be classified into seven categories, each based on different strategies for controlling confounders: matching, reweighting, stratification, multitask learning, tree-based models, meta-learning, and representation learning approaches.

One of the most important applications of machine learning in causal inference lies in estimating heterogeneous treatment effects. Machine learning facilitates accurate and efficient estimation of treatment effect heterogeneity, especially in high-dimensional feature spaces. Athey and Imbens (2016) integrated regression tree algorithms with conventional causal inference frameworks to estimate heterogeneous treatment effects [7]. Wager and Athey (2018) further developed this approach by incorporating random forests to estimate treatment effect heterogeneity [8]. Imai and Ratkovic (2013) framed heterogeneity as a variable selection problem using support vector machines, applying sparse constraints to heterogeneity parameters in classification tasks [34]. Johansson et al. proposed a novel framework for counterfactual inference by integrating neural networks with domain adaptation and representation learning. Hill (2011) introduced Bayesian Additive Regression Trees to model potential outcomes within a Bayesian nonparametric framework, allowing for robust model fitting with minimal prior assumptions [35].

Knaus et al. (2021) categorized machine learning approaches to causal effect heterogeneity into two types: hybrid methods that combine traditional econometric techniques with machine learning and modified versions of existing machine learning algorithms [36]. Athey and Imbens (2019) introduced the GRF framework, with causal forest as a specific case [37]. GRF preserves the honesty property of causal forest while employing alternative node-splitting criteria, thereby improving estimation performance. GRF represents a state-of-the-art approach for estimating heterogeneous treatment effects using machine learning. However, its empirical applications remain relatively limited.

The above literature reveals that although valuable insights have been generated on AI's environmental impacts, most of the existing research remains concentrated on macro-level analyses, particularly at the urban scale. Micro-level studies investigating the role of AI in the sustainable development of manufacturing firms remain scarce. Furthermore, although the impact of digital technologies on SDP has been examined, AI as a distinct technological domain has received relatively little direct attention. This study addresses this gap by empirically examining the relationship between AI applications and firms' SDP from a micro-level perspective. The findings contribute to the growing body of literature on the micro-level effects of AI on corporate sustainability. It also offers theoretical support for promoting China's intelligent manufacturing transformation and advancing corporate sustainability goals.

3. Research Hypotheses

In the context of the intelligent transformation wave, enterprises are increasingly adopting AI technologies in their practices, which gradually demonstrate their value. Existing studies suggest that AI applications enhance corporate performance and help firms achieve competitive advantages [38,39]. In this study, the potential mechanisms through which AI impacts SDP are explored from three perspectives: green innovation, cost savings, and digital transformation.

3.1. Green Innovation Effect

AI can enhance the level of green innovation in enterprises by promoting knowledge overflow. And the improvement of green innovation helps to increase the SDP level of enterprises. The application of AI stimulates enterprises' demand for new knowledge while assisting in the systematic categorization of existing knowledge. This process accelerates the transmission of high-quality information, thereby enriching the organizational knowledge base [40]. AI also facilitates the integration of internal and external knowledge, thereby improving product development and production efficiency. AI significantly enhances green innovation capabilities and reduces pollutant emissions through technological spillover.

Knowledge spillover helps firms acquire cutting-edge external technologies, improve market efficiency, absorb innovative resources, and strengthen innovation capabilities [41]. Enhanced green innovation improves pollution control capabilities, thereby elevating SDP.

In particular, introducing new technologies or fostering cross-departmental knowledge exchange encourages firms to allocate various resources to green R&D, thereby spurring innovation. This scenario increases firms' ability to absorb and apply green technologies. Green innovation enhances resource utilization efficiency and productivity [42]; thus, material inputs and waste are reduced during production processes, enabling cost minimization [43]. Such innovations optimize resource allocation, improve input–output ratios, and elevate SDP. Furthermore, green innovation reduces negative environmental externalities, builds positive stakeholder relationships, and strengthens firms' social reputation by promoting harmony between economic and environmental development. This scenario creates a competitive advantage in environmental leadership, further improving SDP. As a new type of general-purpose technology, AI reshapes R&D processes and innovation activities. Firms adopting AI can influence peer enterprises within the same industry to adopt AI technologies, thereby positively affecting the SDP of manufacturing firms across the board.

Therefore, this study proposes hypothesis H1: AI can improve the SDP level by promoting green innovation in enterprises.

3.2. Cost-Saving Effect

AI can effectively reduce production costs for enterprises through automation technology. AI technologies, such as industrial robots, excel in executing repetitive, highly standardized tasks. These systems operate continuously without interruption; thus, they achieve higher precision and lower error rates than human labor. Graetz and Michaels (2018) demonstrated that automation technologies, represented by industrial robots, reduce variable input factors and enhance labor productivity during production, thereby improving overall production efficiency [44]. After deploying robots, firms optimize production processes and lower marginal costs; they also gradually reduce reliance on low-skilled labor and ultimately replace it entirely [45]. The widespread use of intelligent technologies allows firms to acquire high-quality labor at low costs, thereby enhancing production efficiency through data sharing and organizational flexibility [46].

Low production costs enable firms to allocate a large amount of retained earnings to environmental governance under constant conditions. In particular, manufacturing firms can adjust production costs by applying AI to replace portions of their labor force. As a result, their environmental governance behaviors are influenced and guided to enhance green competitiveness. For instance, Western firms often reduce production costs by outsourcing to developing countries through direct investment or international partnerships. Then, the cost savings can be directed toward various valuable activities, such as improving green product processes [20,21]. In summary, adopting AI technologies in manufacturing generates cost-saving effects, thereby enhancing productivity, reducing costs, and ultimately improving SDP.

Therefore, this study proposes hypothesis H2: AI enhances the SDP of enterprises through a cost-saving effect.

3.3. Digital Transformation Effect

Digital transformation in manufacturing requires the adoption of innovative digital solutions to enhance operational quality and sustainability. As a core technology of the new industrial revolution, AI—characterized by deep learning, human–machine collaboration, open intelligence, and autonomous control—plays a crucial role in facilitating digital

transformation [47]. In the digital economy, data and information resources are essential for improving firms' digital transformation performance. AI enables the automated collection and iterative analysis of data through machine learning algorithms [48]. In particular, this feature enhances the decision-making capabilities of executives and the operational skills of employees, thereby streamlining internal processes and increasing efficiency. Moreover, the real-time analysis of market demands and user data facilitates precision marketing, thereby helping firms understand product and market dynamics comprehensively and adapt swiftly to changes.

Furthermore, digital transformation improves resource utilization efficiency. First, digital transformation aligns data flows with capital, technology, and talent flows, thereby promoting intensive and efficient production methods [49]. Second, it enables intelligent resource allocation and parameter adjustments through real-time monitoring, thereby fostering resource recycling and reducing environmental impact [50]. These outcomes enhance environmental governance effectiveness and SDP.

Therefore, this study proposes hypothesis H3: AI promotes the improvement of SDP by accelerating the digital transformation of enterprises

4. Model Setup

4.1. DID Model

The DID model is a causal inference method based on natural experimental design, whose core is to estimate the net effect of policies or interventions by subtracting external factors twice. To minimize the selection bias of AI proxy indicators, the existing literature has examined the environmental benefits of AI based on DID method and APIZ policy [51,52]. It can be seen from the above that 18 cities in China have been approved to be built into AIPZ. The construction of these pilot areas has provided important support for the development of the AI industry. In this paper, the listed enterprises headquartered in these pilot cities are set as the treatment group, while the listed enterprises headquartered in other cities are set as the control group. To verify how AI affects enterprises' SDP, the following multi-period DID model is established:

$$SDP_{it} = \alpha_0 + \alpha_1 AIPZ * Time_{it} + \alpha_2 CV_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (1)$$

where i and t denote the enterprise and the year, respectively, *SDP* denotes the SDP of the enterprise, and *AIPZ*Time* denotes the AIPZ policy. In particular, *AIPZ* is a dummy variable of the treatment group (equals 1 for pilot enterprises and 0 for other enterprises). *Time* is the time dummy variable representing the AIPZ policy implementation year: 1 is assigned to time after the AIPZ policy implementation, and 0 is assigned to the rest. *CV* is the control variable matrix. μ denotes the individual fixed effects, and γ denotes the year fixed effects. The coefficient size of *AIPZ*Time* reflects the degree of impact of AI on enterprise SDP. If the coefficient of *AIPZ*Time* is significantly positive, it can indicate that China's implementation of AIPZ policy has promoted the improvement of pilot enterprise SDP, that is, AI can have a positive impact on SDP.

4.2. Data Sources and Indicator Selection

4.2.1. Data Sources

Due to the fact that manufacturing is the main industry for energy consumption and also an important subject for the application of AI technology, we select Chinese A-share listed manufacturing enterprises from 2007 to 2022 as the sample to test the effect of AI on enterprise SDP. Before conducting a regression analysis, this paper screens out sample companies that have been marked as special treatment by the stock exchange, including

ST, PT, and *ST companies, and deletes samples with missing data for the main variables. In addition, continuous variables are subjected to 1% upward and downward tailing. In the end, this study obtains 16,515 observation samples. The company characteristics data are obtained from the China Stock Market and Accounting Research (CSMAR) and CNDeepData databases.

4.2.2. Indicator Selection

This paper measures the SDP of enterprises from two aspects [53]: financial performance and environmental performance. We use return on assets to measure the financial performance level [54–56]. The environmental score in Bloomberg's ESG scoring system is a rating of a company's environmental performance indicators, such as resource consumption, pollutant emissions, and waste disposal. Therefore, this study uses the environmental score from Bloomberg's ESG rating system as a proxy variable for corporate environmental performance. In addition, this study standardizes the financial and environmental performance of enterprises, limiting the range of the two indicators to being from 0 to 1. Subsequently, drawing on the practices of Xie and Zhu (2021) [14], Xi and Zhao (2022) [57], we use the entropy weight method to calculate the weights of financial performance and environmental performance, and ultimately obtain the SDP of the enterprise. The entropy weight method determines weights by calculating information entropy, relying entirely on the degree of variation of the data itself, avoiding subjective judgments and making weight determination more objective and scientific. In contrast, principal component analysis may require more subjective judgments and assumptions when determining weights. In addition, the entropy weight method is suitable for situations where there are significant differences between indicators, and can better reflect the amount of information provided by different indicators. When there are significant differences in the data of certain indicators, the entropy weight method can more accurately measure these differences and assign higher weights. Principal component analysis may not be as flexible and accurate as the entropy weight method in dealing with such problems. This study first calculates the weights of financial performance and environmental performance using the entropy weight method, and then standardizes the variables of environmental performance and financial performance. The standardized variable values are multiplied by the corresponding weights and added together to obtain the SDP of the enterprises.

Based on the existing literature [57], I select some enterprise-level control variables that will affect enterprise SDP, as shown in Table 1 below.

Table 1. Variable description and descriptive statistics.

Variable	Symbol	Definition	Mean	SD
Sustainable Development Performance	*SDP*	Calculated based on entropy method	0.5933	0.0683
Asset liability ratio	*Lev*	Ln (ratio of total liabilities to total assets)	−1.0544	0.6032
Tobin's q value	*Tobinq*	Ln (market value of debt and equity to replacement cost of total assets)	0.6332	0.4886
Labor productivity	*Lp*	Ln (operating income to the number of employees)	13.7111	0.7162
Cash flow	*Cash*	Ln (ratio of net cash flow from operating activities to total assets)	−1.8781	0.7061

Table 1. *Cont.*

Variable	Symbol	Definition	Mean	SD
Enterprise size	*Size*	Ln (total enterprise assets)	22.086	1.1913
Net Profit Margin	*Npm*	Ln (net profit to operating income)	−3.0530	1.1055
Number of employees	*Ne*	Ln (number of employees)	7.7984	1.1499

5. Empirical Result Analysis

5.1. Baseline Results

Based on the data of Chinese manufacturing listed companies from 2007 to 2022, combined with the DID model, this paper empirically tests the relationship between AI and SDP. Table 2 reports the impact of AI on corporate SDP. When control variables are not included and only individual and year effects are controlled for, the regression coefficient of the DID model is 0.0146, which is statistically significant at the 1% level. This finding suggests that AI significantly impacts SDP. After control variables are added, the regression coefficient of AI on SDP is 0.0139, indicating that the AIPZ policy has increased the SDP level of pilot enterprises by 1.39%. The above result also indicates that high levels of AI adoption are associated with great improvements in SDP. By introducing AI technology, enterprises have achieved a transformation and upgrading of the entire process of production, management, and service, profoundly changing their operational mode and development path [51,52]. This not only improves their production efficiency and market competitiveness, but also reduces energy consumption and environmental pollution, thereby enhancing their SDP. Therefore, vigorously promoting the application of AI in enterprise production and operation may be an important way to promote the sustainable development of enterprises.

Table 2. Overall impact of AI on SDP.

	(1)	(2)	(3)
	SDP	**SDP**	**SDP**
*AIPZ*Time*	0.0146 ***	0.0128 ***	0.0139 ***
	(0.00178)	(0.00192)	(0.00175)
Lev		−0.0253 ***	−0.0195 ***
		(0.00113)	(0.00140)
Tobinq		−0.00198	−0.00225
		(0.00123)	(0.00143)
Lp		0.0106 ***	0.00578 ***
		(0.00115)	(0.00178)
Cash		0.0379 ***	0.0284 ***
		(0.00452)	(0.00458)
Size		0.00222 *	0.00858 ***
		(0.00123)	(0.00199)
Npm		0.00319 ***	0.00227 **
		(0.000512)	(0.00108)
Ne		0.0158 ***	0.0162 ***
		(0.00115)	(0.00195)
ID effects	YES	NO	YES
Year effects	YES	YES	YES
Observations	16,515	16,515	16,515
R-squared	0.581	0.111	0.599

Note: Robust standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.2. Robustness Check

The above empirical analysis confirms that AI has a positive impact on improving enterprise SDP. However, it is unclear whether the choice of DID model is appropriate and whether other policies similar to AIPZ interfere with the results of this paper. To further enhance the robustness of the main conclusion of this study, a series of robustness tests are conducted.

5.2.1. Parallel Trend Test

This paper performs a parallel trend test based on the event study methodology. The results are shown in Table 3. Before policy implementation, no significant differences are found in the SDP of pilot and nonpilot firms. Although the coefficient in the policy implementation year is not significant, the DID coefficients for the first to third years after policy implementation are all significantly positive. This finding indicates that the AI policy does not immediately impact SDP in the first year, but rather it shows significant effects starting one year after implementation. This observation suggests a delayed impact of AI policy on corporate SDP. The results validate the parallel trend assumption, confirming that the multiperiod DID model is reasonable and reliable.

Table 3. Results of the parallel trend test.

	(1)	**(2)**
	SDP	***SDP***
$AIPZ*Time_{-2}$	0.00112	0.00158
	(0.00251)	(0.00246)
$AIPZ*Time_{-1}$	0.00135	0.00181
	(0.00224)	(0.00221)
$AIPZ*Time_{0}$	0.000775	0.00129
	(0.00261)	(0.00257)
$AIPZ*Time_{1}$	0.0211 ***	0.0207 ***
	(0.00287)	(0.00280)
$AIPZ*Time_{2}$	0.0128 ***	0.0121 ***
	(0.00222)	(0.00218)
$AIPZ*Time_{3}$	0.0210 ***	0.0220 ***
	(0.00644)	(0.00644)
CV	NO	YES
ID effects	YES	YES
Year effects	YES	YES
Observations	16,515	16,515
R-squared	0.554	0.572

Note: Robust standard errors are in parentheses; *** $p < 0.01$.

5.2.2. Placebo Test

Following the practice of La Ferrara et al. (2012) [58], this paper conducts a placebo test to ensure that the impact of AI on SDP is not driven by other random factors. I perform 500 placebo tests and randomly select multiple time points are selected as "virtual policy implementation" years. The results are displayed in Figure 1. The mean regression coefficient is close to 0 and is significantly smaller than the benchmark coefficient, with the P-values being greater than 0.1. This finding indicates that the impact of AI policy on SDP is not due to random factors, and the results obtained above are robust.

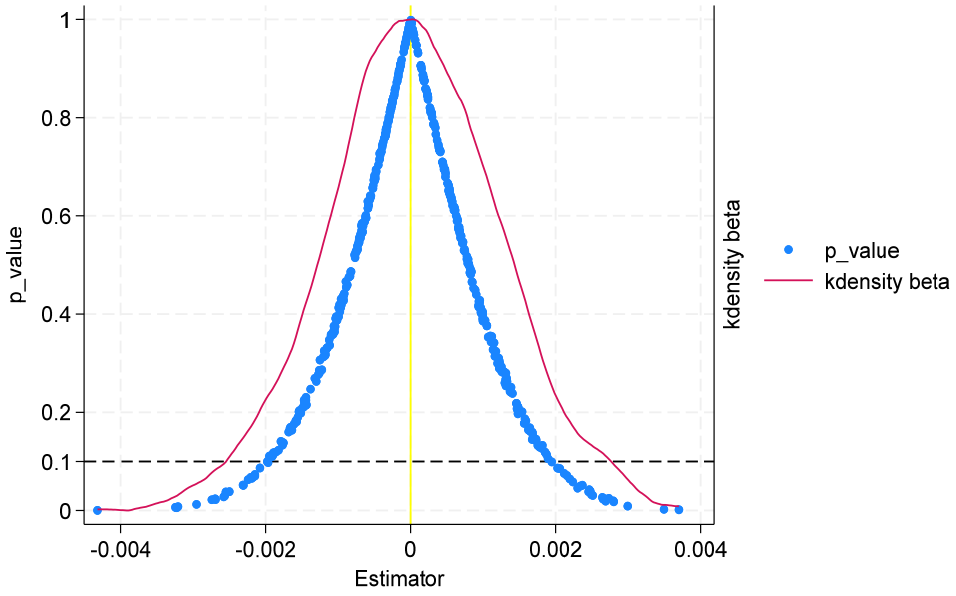


Figure 1. Placebo test.

5.2.3. Replacing the Explanatory Variable

In this study, I reference the work of Yao et al. (2024) [59] by conducting a text analysis of annual reports to identify the frequency of AI-related keywords. I log-transform the frequency of these keywords to form an AI intensity measure (lnAI). The larger the lnAI is, the higher the AI adoption level in the firm is. I replace the explanatory variable with lnAI and performed regression analysis, as shown in Table 4. Regardless of whether control variables are included, the coefficient of lnAI is significantly positive, indicating that the level of AI, as measured by keyword frequency, significantly enhances corporate SDP.

Table 4. Replaced explanatory variable.

	(1)	**(2)**
	SDP	***SDP***
lnAI	0.0063 ***	0.0043 ***
	(0.0012)	(0.0012)
CV	NO	YES
ID effects	YES	YES
Year effects	YES	YES
Observations	16,515	16,515
R-squared	0.552	0.57

Note: Robust standard errors are in parentheses; *** $p < 0.01$.

5.2.4. Exclusion of Similar Policy

In our research scope, China implemented the Smart City pilot policy in 2012. Smart cities, characterized by innovation-driven and environmental sustainability, foster the rise of green and technology-intensive industries, such as AI and big data. Consequently, these industries provide the impetus for green innovation activities in firms. I introduce a dummy variable (SC × Time) for the Smart City policy to eliminate the potential interference of the Smart City policy. The *SC* variable indicates whether the firm is located in a pilot city, and the *Time* variable represents the year of the policy implementation. As shown in Table 5, the DID results indicate that after controlling for the impact of the Smart City policy, AI still positively influences corporate SDP by adding the dummy variable into the baseline model.

Table 5. Exclusion of similar policy.

	(1)	(2)
	SDP	***SDP***
*AIPZ*Time*	0.0148 ***	0.0141 ***
	(0.00178)	(0.00175)
CV	NO	YES
ID effects	YES	YES
Year effects	YES	YES
Observations	16,515	16,515
R-squared	0.581	0.599

Note: Robust standard errors are in parentheses; *** $p < 0.01$.

5.2.5. Other Robustness Tests

The sample in this study spans a long period and includes many unobservable confounding factors, which may affect the estimation accuracy of the DID model. Following Zhou et al. (2023) [60], I adjust the sample time to 2016–2021 and re-estimate the model to improve the efficiency of DID estimation. The regression results are shown in column 1 of Table 6, where the AI coefficient remains significant. I also added the interaction term of the industry fixed effects and year fixed effects to the baseline model to eliminate potential confounders at the industry level. The regression results in column 2 of Table 6 show that the AI coefficient remains significant. It is considered that the selection of AIPZ pilot cities is not random, but determined by the government based on factors such as the city's economic development, technological innovation, infrastructure construction, and industrial structure. Therefore, to address the endogeneity issue that may arise from self-selection in the sample, this study uses a propensity score matching model to find the "counterfactual group" of AIPZ cities to solve this selection bias problem. This study uses control variables as covariates to estimate propensity scores for the experimental group and control group sample companies through logistic regression. Based on the estimation results, samples that are not included in the matching group are excluded and the regression is conducted again. The result is shown in column (3), and the AI coefficient is still significantly positive.

Table 6. Other robustness tests.

	(1)	(2)	(3)
	SDP	***SDP***	***SDP***
*AIPZ*Time*	0.011 ***	0.0139 ***	0.0152 ***
	(0.0018)	(0.00174)	(0.0019)
CV	YES	YES	YES
ID effects	YES	YES	YES
Year effects	YES	YES	YES
Observations	10,085	16,515	16,515
R-squared	0.705	0.599	0.572

Note: Robust standard errors are in parentheses; *** $p < 0.01$.

5.2.6. GRF Model Robustness Check

Athey et al. (2019) proposed the GRF model [9], which can be applied to quantile regression, causal forests, instrumental variable models, and panel models. In this study, GRF is used to estimate the heterogeneity of policy effects, following the methodology of Knittel and Stolper (2021) [61]. The basic steps for using GRF to estimate treatment effects are as follows: (1) A subset is randomly sampled from the full sample without replacement. (2) The subset is split into two sets: training and estimation sets. (3) A decision tree is constructed based on the training set and splitting criteria. (4) The samples

are matched from the estimation set to the decision tree. Then, the treatment effects for each leaf node are estimated based on the matched samples. (5) Steps 1–4 are repeated for 2000 decision trees. (6) The average treatment effect is calculated for each individual. The GRF model's estimation is performed using the "Causal Forests" command in the R package (https://www.r-project.org/) with default parameters. The results in Table 7 show that as the number of decision trees increases from 500 to 2000, the average treatment effect of AI on corporate SDP remains stable at around 0.004 with no change in the standard deviation. This observation suggests that the model's precision is adequate. The results in Table 7 also confirm that the GRF estimates are stable. Although the GRF estimates are slightly lower than the DID results in Table 2, they still indicate that AI enhances corporate SDP. The basic principles of the DID model and GRF model are not the same, so their estimated coefficient sizes are not comparable. However, the core impact coefficients estimated by DID and GRF models are significantly positive, which can mutually verify the reliability of the positive impact of AI on the SDP of enterprises.

Table 7. Causal identification using GRF.

	(1)	(2)	(3)	(4)
	SDP	***SDP***	***SDP***	***SDP***
*AIPZ*Time*	0.00445 ***	0.00466 ***	0.00445 ***	0.00472 ***
	(0.00233)	(0.00233)	(0.00233)	(0.00233)
Clustered	NO	NO	NO	YES
Tree	500	1000	2000	2000
Model	Causal Forest	Causal Forest	Causal Forest	Causal Forest

Note: Robust standard errors are in parentheses; *** $p < 0.01$.

5.3. Mechanism Analysis

I extend the baseline model (1) by incorporating mediating variables to test the mechanisms through which AI impacts the SDP of manufacturing firms.

$$Med_{it} = \beta_0 + \beta_1 AIPZ * Time_{it} + \beta_2 CV_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (2)$$

Med refers to the mediating variables, which include green innovation (GI), cost savings (cost), and digital transformation (DT). Following the existing literature, this study uses the logarithm of the number of green patent applications by enterprises as a proxy for green innovation. Given that the management expense ratio primarily reflects agency costs [62], this study uses the proportion of enterprise management expenses to main business income to represent the cost of the enterprise as a proxy for cost-saving effects. Following the method of Shang et al. (2023) [63], this study analyzes the frequency of keywords related to "digital transformation" in annual reports by taking the logarithm of the keyword frequency to measure the extent of DT. Table 8 presents the results of model (2), where the DID coefficients for all mediating variables are significant. When the explanatory variable is *GI*, the DID coefficient is 0.022 with a significance level of 10%. When the explanatory variable is cost, the DID coefficient is -0.011 with a significance level of 1%. When the explanatory variable is *DT*, the DID coefficient is 0.0801 with a significance level of 1%. The above empirical results demonstrate that AI can effectively enhance green innovation, generate cost-saving effects, and promote digital transformation of enterprises. In addition, existing literature has found that green innovation, production costs, and digital transformation play a positive role in promoting sustainable development of enterprises [20,21,50,64]. Therefore, this finding confirms that AI improves cost-saving, green innovation, and digital transformation. As a result, the corporate SDP is enhanced, thereby verifying the hypotheses H1–H3 in this study.

Table 8. Mechanism test.

	(1)	(2)	(3)
	GI	***Cost***	***DT***
*AIPZ*Time*	0.022 *	−0.011 ***	0.0801 ***
	(0.012)	(0.0017)	(0.0241)
CV	YES	YES	YES
ID effects	YES	YES	YES
Year effects	YES	YES	YES
Observations	16,515	16,515	16,515
R-squared	0.724	0.638	0.767

Note: Robust standard errors are in parentheses; * $p < 0.1$, *** $p < 0.01$.

5.4. Moderation Effect of CEO Duality

The internal governance structure of a company plays a crucial role in influencing corporate behavior. For example, whether the roles of the CEO and the chairman are held by the same individual may impact the effect of AI on SDP. We introduced a dummy variable (Dual) to capture CEO duality. When the CEO and the chairman are the same person, Dual is set to 1; otherwise, it is set to 0. This study adds the interaction term of *Dual* and *AIPZ*Time* to model (1). Table 9 shows the moderation effect of CEO duality. The coefficient for the interaction term *AIPZ*Time*Dual* is significantly negative, suggesting that CEO duality has a negative moderating effect. When the CEO holds both the CEO and the chairman roles, the CEO possesses great managerial autonomy, which may lead to biased decision making focused on short-term financial performance. Thus, the positive impact of AI on SDP is undermined. By contrast, when the CEO and the chairman roles are separate, the CEO is subject to supervision and evaluation by the board, and decisions are likely to align with the firm's long-term development. In this situation, the CEO may encourage the use of AI technology to address environmental issues and ensure the sustainability of the company. This scenario can effectively support sustainable practices. Thus, CEO duality weakens the positive effect of AI on SDP.

Table 9. Regulatory analysis.

	(1)	(2)
	SDP	***SDP***
*AIPZ*Time*Dual*	−0.00761 **	−0.00631 **
	(0.003)	(0.00293)
*AIPZ*Time*	0.0171 ***	0.0161 ***
	(0.002)	(0.00204)
Dual	−0.0008	−0.00209
	(0.0015)	(0.00152)
CV	NO	YES
ID effects	YES	YES
Year effects	YES	YES
Observations	16,177	16,177
R-squared	0.581	0.6

Note: Robust standard errors are in parentheses; ** $p < 0.05$, *** $p < 0.01$.

5.5. Heterogeneity Analysis

Traditional linear regression models primarily focus on the average treatment effect of policies, whereas the GRF model can estimate the average and individual treatment effects. Figure 2 displays the distribution of individual treatment effect estimates for the impact of AI on the SDP of listed companies. Overall, the individual treatment effects

center around the average treatment effect, showing considerable variation. The majority of the samples have treatment effects between 0.001 and 0.009, but the range for the entire sample spans from −0.01 to 0.02. A small number of firms even show negative treatment effects, suggesting that AI may suppress SDP in certain cases. This outcome can be due to the fact that AI adoption, which leads to expanded production scales, may result in increased environmental pollution, negatively affecting SDP.

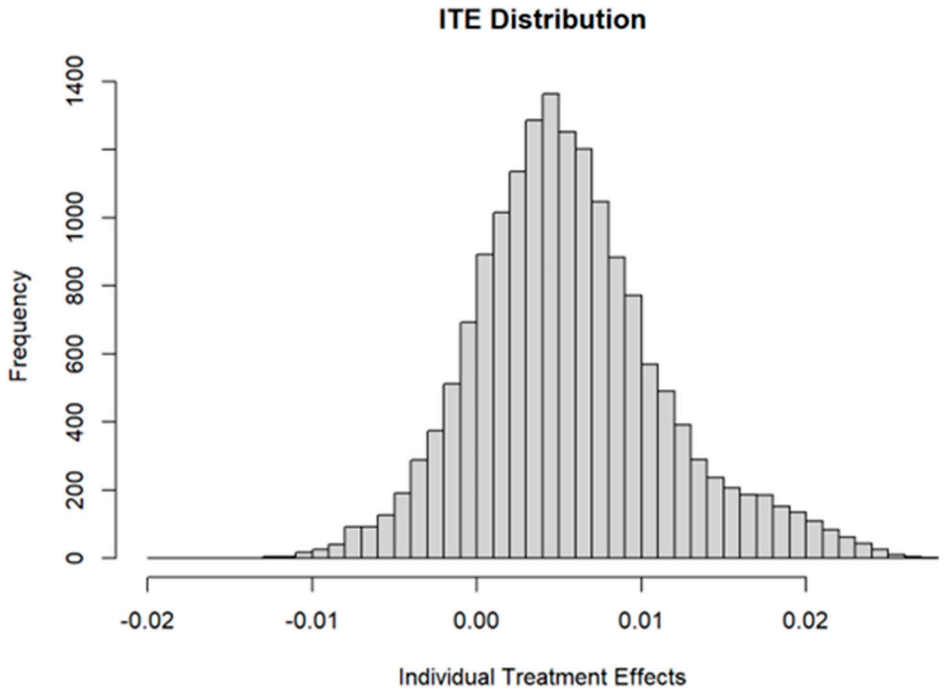


Figure 2. Distribution of AI's treatment effect on SDP.

I divide the sample based on ownership type into state-owned and non–state-owned firms, as shown in columns 1 and 2 of Table 10 to explore the heterogeneous effects of AI. The results indicate that AI has a more significant positive effect on SDP in state-owned enterprises than non–state-owned ones. The possible reason is that, in the context of dual carbon goals, state-owned enterprises are highly attuned to the direction set by AI and green policies. Hence, they are very proactive in adopting intelligent and green transformations. Therefore, with strong government support, state-owned enterprises are likely to adopt AI applications, thereby improving their SDP.

Table 10. Subsample heterogeneity test using GRF.

Variable	(1) State-Owned	(2) Non–State-Owned	(3) Light Pollution	(4) Heavy Pollution
*AIPZ*Time*	0.0121 ***	0.0086 ***	0.0036 ***	0.0055 ***
	(0.00262)	(0.00348)	(0.00187)	(0.00288)
Obs	5243	11,035	10,420	6064
Tree	2000	2000	2000	2000
Clustered	YES	YES	YES	YES

Note: Robust standard errors are in parentheses; *** $p < 0.01$.

Additionally, I categorize the sample based on pollution levels into high-polluting and low-polluting firms, as shown in columns 3 and 4 of Table 10. The results show that the positive effect of AI on SDP in high-polluting firms is stronger than that in low-polluting ones. This outcome is likely because high-polluting firms rely heavily on capital, energy-intensive resources, and large-scale machinery. The introduction of AI can help these firms

upgrade their existing equipment to energy-efficient, smart systems, thereby improving energy efficiency, reducing resource waste, and significantly enhancing their SDP.

6. Conclusions

AI has become deeply integrated into various aspects of production and management in manufacturing firms, significantly impacting their SDP. In this study, multi-period DID and GRF models were used to empirically analyze the effects of AI on corporate SDP and its underlying mechanisms. The key conclusions are as follows: (1) AI adoption positively influences the SDP of manufacturing enterprises. (2) AI enhances SDP through a cost-saving effect, green innovation, and digital transformation. In particular, AI facilitates green innovation and resource efficiency while driving digitalization, all of which contribute to improving the SDP of enterprises. CEO duality (i.e., when the CEO also holds the chairman position) weakens the positive impact of AI on SDP of enterprises. (3) The positive impact of AI on SDP is highly pronounced in state-owned enterprises and heavily polluting firms. State-owned enterprises, benefiting from strong government support and policy incentives, are likely to adopt AI and green technologies, leading to great improvements in SDP. Similarly, high-polluting firms, which heavily rely on energy-intensive processes, benefit from AI adoption because it helps optimize production processes and reduce environmental impact.

Based on data from European or global countries, scholars have confirmed the positive role of AI in the field of sustainable development [65–67], which is consistent with the main findings of this study. AI is becoming a revolutionary force and has made significant progress in the field of sustainable development. Given the benefits of AI, recent research emphasizes the need for governments around the world to develop comprehensive AI strategies and prioritize achieving sustainable development goals [68]. The research findings of this paper also remind AI practitioners and policymakers in other countries to prioritize progress towards sustainable development goals, especially exploring the potential of AI in strengthening and accelerating these efforts. On the basis of these findings, this study provides several policy recommendations:

(1) For enterprises: First, firms should enhance their AI capabilities and continue to improve their green technology innovation. Companies can integrate green innovation resources, accelerate the transformation of sustainable development results, and ultimately improve SDP by broadening the scope and depth of AI applications. Second, firms with low AI adoption levels should overcome existing biases, actively learn to apply AI technologies, and connect internal and external resources to drive sustainable development. Third, given the negative moderating effect of the CEO duality on the relationship between AI and corporate SDP, companies can implement a governance model where the chairman and general manager are separated, and reasonably control the proportion of executive shareholding to avoid the negative impact of excessive power concentration and short-term interest pursuit on SDP investment.

(2) For government: The government should invest considerably in fundamental AI research and key technology development while fostering collaboration between enterprises, academia, and research institutions to enhance innovation. Additionally, the government should offer clear policies that encourage AI adoption, ensure transparent policy implementation, and protect intellectual property rights. Strengthening the innovation ecosystem can boost technological advancements and, ultimately, support firms in achieving sustainable development goals. For high-polluting enterprises, the government should increase support for environmental protection technology, guide financial institutions to provide them with low-interest loans or green financial products, reduce financing costs, alleviate financing constraints, and enable them to

have more resources to invest in green transformation and SDP construction. For non-state-owned enterprises, the government needs to further improve its technology innovation incentive policies, encourage them to conduct cutting-edge research and applications in the field of AI and SDP integration, and create industry benchmark cases. Finally, the government can establish cross-regional communication and cooperation mechanisms to promote experience sharing between AI pilot zones and non-pilot zone enterprises, in order to enhance the overall SDP performance of manufacturing enterprises.

There are still some research limitations in this paper. Although the headquarters of many manufacturing enterprises are located in AIPZ cities, their actual plant distribution may be cross-regional, which leads to the deviation of policy identification from the actual behavior and affects the explanatory power set by the DID model. Due to the availability of data on the geographical location of enterprise factories, this study can only rely on existing literature to select pilot enterprises based on the location of the enterprise headquarters [51,52]. In future research, the geographical location of core factories of enterprises should be collected as much as possible. In addition, there is some controversy over whether ROA and ESG environmental scores can fully reflect a company's financial and environmental performance when measuring SDP, which is also a limitation of this study. Similarly, using ESG ratings as a proxy indicator for corporate environmental performance may also introduce unobserved biases. In future research, other comprehensive variables should be used as proxy variables for SDP, such as the green total factor productivity of enterprises. Through parallel trend testing, this paper finds that there is a lag effect of AI on enterprise SDP, but this study does not further analyze whether the impact of AI on mediating variables also has a lag effect. In future research, the dynamic effects of the impact mechanism of AI should be analyzed, in order to obtain more interesting results.

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References

1. Zhou, C.B.; Qi, S.Z.; Li, Y.K. Environmental policy uncertainty and green transformation dilemma of Chinese enterprises. *J. Environ. Manag.* **2024**, *370*, 122891. [CrossRef] [PubMed]
2. Ye, Z.; Yang, J.; Zhong, N.; Tu, X.; Jia, J.; Wang, J. Tackling environmental challenges in pollution controls using artificial intelligence: A review. *Sci. Total Environ.* **2020**, *699*, 134279. [CrossRef] [PubMed]
3. Liang, P.; Sun, X.; Qi, L. Does artificial intelligence technology enhance green transformation of enterprises: Based on green innovation perspective. *Environ. Dev. Sustain.* **2024**, *26*, 21651–21687. [CrossRef]
4. Hadi, S.; Baskaran, S. Examining sustainable business performance determinants in Malaysia upstream petroleum industry. *J. Clean. Prod.* **2021**, *294*, 126231. [CrossRef]
5. Wang, Y.R. The Impact of Digital Strategic Orientation on Enterprise Sustainable Performance Against the Background of 2030 Sustainable Performance Goal. *Math. Probl. Eng.* **2022**, *8*, 2263222. [CrossRef]
6. Su, Y.L.; Wu, J.H. Digital transformation and enterprise sustainable development. *Financ. Res. Lett.* **2024**, *60*, 104902. [CrossRef]

7. Athey, S.; Imbens, G. Recursive Partitioning for Heterogeneous Causal Effects. *Proc. Natl. Acad. Sci. USA* **2016**, *113*, 7353–7360. [CrossRef]
8. Wager, S.; Athey, S. Estimation and inference of heterogeneous treatment effects using random forests. *J. Am. Stat. Assoc.* **2018**, *113*, 1228–1242. [CrossRef]
9. Athey, S.; Tibshirani, J.; Wager, S. Generalized Random Forests. *Ann. Stat.* **2019**, *47*, 1148–1178. [CrossRef]
10. Harris, J.M. Sustainability and sustainable development. *Int. Soc. Ecol. Econ.* **2003**, *1*, 1–12.
11. Bansal, P. Evolving sustainably: A longitudinal study of corporate sustainable development. *Strateg. Manag. J.* **2005**, *26*, 197–218. [CrossRef]
12. Elkington, J. Towards the sustainable corporation: Win-win-win business strategies for sustainable development. *Calif. Manag. Rev.* **1994**, *36*, 90–100. [CrossRef]
13. Krajnc, D.; Glavič, P. How to compare companies on relevant dimensions of sustainability. *Ecol. Econ.* **2005**, *55*, 551–563. [CrossRef]
14. Xie, X.M.; Zhu, Q.W. How Can Green Innovation Solve the Dilemmas of Harmonious Coexistence? *J. Manag. World* **2021**, *1*, 128–149.
15. Aksoy, M.; Yilmaz, M.K.; Tatoglu, E.; Basar, M. Antecedents of corporate sustainability performance in Turkey: The effects of ownership structure and board attributes on non-financial companies. *J. Clean. Prod.* **2020**, *276*, 124284. [CrossRef]
16. Aftab, J.; Veneziani, M.; Sarwar, H.; Ishaq, M.I. Organizational ambidexterity, firm performance, and sustainable development: Mediating role of entrepreneurial orientation in Pakistani SMEs. *J. Clean. Prod.* **2022**, *367*, 132956. [CrossRef]
17. Fernando, Y.; Jabbour, C.J.C.; Wah, W.X. Pursuing green growth in technology firms through the connections between environmental innovation and sustainable business performance: Does service capability matter? *Resour. Conserv. Recycl.* **2019**, *141*, 8–20. [CrossRef]
18. Al Koliby, I.S.; Mohd Suki, N.; Abdullah, H.H. Linking knowledge acquisition, knowledge dissemination, and manufacturing SMEs' sustainable performance: The mediating role of knowledge application. *Bottom Line* **2022**, *35*, 185–202. [CrossRef]
19. Jia, J.; Li, Z. Does external uncertainty matter in corporate sustainability performance? *J. Corp. Financ.* **2020**, *65*, 101743. [CrossRef]
20. Li, J.; Ji, L.; Zhang, S.; Zhu, Y. Digital technology, green innovation, and the carbon performance of manufacturing enterprises. *Front. Environ. Sci.* **2024**, *12*, 1384332. [CrossRef]
21. Li, X.; Tian, Q. How does usage of robot affect corporate carbon emissions? Evidence from China's manufacturing sector. *Sustainability* **2023**, *15*, 1198. [CrossRef]
22. Duan, D.; Chen, S.; Feng, Z.; Li, J. Industrial robots and firm productivity. *Struct. Change Econ. Dyn.* **2023**, *67*, 388–406. [CrossRef]
23. Jin, X.Y.; Zhang, W.F. Artificial intelligence and enterprise pollution reduction: Environmental effects of intelligent governance. *China Popul. Resour. Environ.* **2023**, *33*, 138–145.
24. Lin, B.; Xu, C. Enhancing energy-environmental performance through industrial intelligence: Insights from Chinese prefectural-level cities. *Appl. Energy* **2024**, *365*, 123245. [CrossRef]
25. Zhao, C.; Wang, L.; Zhou, C. Impact of Industrial Intelligence on China's Urban Land Green Utilization Efficiency. *Land* **2024**, *13*, 1312. [CrossRef]
26. Yang, H.; Li, L.; Liu, Y. The effect of manufacturing intelligence on green innovation performance in China. *Technol. Forecast. Soc. Change* **2022**, *178*, 121569. [CrossRef]
27. Nie, F.; Hu, H.L.; Li, L. How can industrial robots promote green production? Evidence from Chinese micro-firms. *Ind. Econ. Res.* **2022**, *4*, 1–14.
28. Chen, M.; Wang, S.; Wang, X. How Does Artificial Intelligence Impact Green Development? Evidence from China. *Sustainability* **2024**, *16*, 1260. [CrossRef]
29. Barney, J. Firm resources and sustained competitive advantage. *J. Manag.* **1991**, *17*, 99–120. [CrossRef]
30. Lyytinen, K.; Yoo, Y.; Boland Jr, R.J. Digital product innovation within four classes of innovation networks. *Inf. Syst. J.* **2016**, *26*, 47–75. [CrossRef]
31. Jiang, X.; Jiang, X.; Sun, W.; Fan, W. How do manufacturing firms manage artificial intelligence to drive iterative product innovation? *IEEE Trans. Eng. Manag.* **2023**, *71*, 6090–6102. [CrossRef]
32. Shah, T.R. Can big data analytics help organisations achieve sustainable competitive advantage? A developmental enquiry. *Technol. Soc.* **2022**, *68*, 101801. [CrossRef]
33. Friedman, N.; Ormiston, J. Blockchain as a sustainability-oriented innovation? Opportunities for and resistance to Blockchain technology as a driver of sustainability in global food supply chains. *Technol. Forecast. Soc. Change* **2022**, *175*, 121403. [CrossRef]
34. Imai, K.; Ratkovic, M. Estimating treatment effect heterogeneity in randomized program evaluation. *Ann. Appl. Stat.* **2013**, *7*, 443–470. [CrossRef]
35. Hill, J.L. Bayesian nonparametric modeling for causal inference. *J. Comput. Graph. Stat.* **2011**, *20*, 217–240. [CrossRef]
36. Knaus, M.C.; Lechner, M.; Strittmatter, A. Machine learning estimation of heterogeneous causal effects: Empirical Monte Carlo evidence. *Econom. J.* **2021**, *24*, 134–161. [CrossRef]

37. Athey, S.; Imbens, G.W. Machine learning methods that economists should know about. *Annu. Rev. Econ.* **2019**, *11*, 685–725. [CrossRef]
38. Ferreira, J.J.M.; Fernandes, C.I.; Ferreira, F.A.F. To be or not to be digital, that is the question: Firm innovation and performance. *J. Bus. Res.* **2019**, *101*, 583–590. [CrossRef]
39. Wang, K.L.; Sun, T.T.; Xu, R.Y. The impact of artificial intelligence on total factor productivity: Empirical evidence from China's manufacturing enterprises. *Econ. Change Restruct.* **2023**, *56*, 1113–1146. [CrossRef]
40. Liu, J.Q.; Sun, P.Y. Open Competition, Intelligent Manufacturing and Consumer Welfare Effect. *Stat. Res.* **2023**, *40*, 42–57.
41. Audretsch, D.B.; Belitski, M. The role of R&D and knowledge spillovers in innovation and productivity. *Eur. Econ. Rev.* **2020**, *123*, 103391.
42. Woo, C.; Chung, Y.; Chun, D.; Han, S.; Lee, D. Impact of green innovation on labor productivity and its determinants: An analysis of the Korean manufacturing industry. *Bus. Strategy Environ.* **2014**, *23*, 567–576. [CrossRef]
43. Tu, Y.; Wu, W. How does green innovation improve enterprises' competitive advantage? The role of organizational learning. *Sustain. Prod. Consum.* **2021**, *26*, 504–516. [CrossRef]
44. Graetz, G.; Michaels, G. Robots at work. *Rev. Econ. Stat.* **2018**, *100*, 753–768. [CrossRef]
45. Zhao, Y.; Said, R.; Ismail, N.W.; Hamzah, H.Z.; Chen, H. Effect of industrial robots on employment in China: An industry level analysis. *Comput. Intell. Neurosci.* **2022**, *2022*, 2267237. [CrossRef]
46. Zhu, Z.J.; Yuan, Y.M.; Jiao, J.J. Industrial Automation and Manufacturing Innovation Behavior. *China Ind. Econ.* **2022**, *7*, 82–104.
47. Zeba, G.; Dabić, M.; Čičak, M.; Daim, T.; Yalcin, H. Technology mining: Artificial intelligence in manufacturing. *Technol. Forecast. Soc. Change* **2021**, *171*, 120971. [CrossRef]
48. Ma, H.J.; Lin, Y.; Su, Z. Artificial Intelligence Affordance, Intelligent Manufacturing Platform Value Co-Creation and Digital Transformation Performance of Manufacturing Enterprises. *China Ind. Econ.* **2024**, *6*, 155–173.
49. Wen, H.; Lee, C.C.; Song, Z. Digitalization and environment: How does ICT affect enterprise environmental performance? *Environ. Sci. Pollut. Res.* **2021**, *28*, 54826–54841. [CrossRef]
50. Wei, Z.; Sun, L. How to leverage manufacturing digitalization for green process innovation: An information processing perspective. *Ind. Manag. Data Syst.* **2021**, *121*, 1026–1044. [CrossRef]
51. Mijit, R.; Hu, Q.; Xu, J.; Ma, G. Greening through AI? The impact of Artificial Intelligence Innovation and Development Pilot Zones on green innovation in China. *Energy Econ.* **2025**, *146*, 108507. [CrossRef]
52. Huang, Y.; Liu, S.; Gan, J.; Liu, B.; Wu, Y. How does the construction of new generation of national AI innovative development pilot zones drive enterprise ESG development? Empirical evidence from China. *Energy Econ.* **2024**, *140*, 108011. [CrossRef]
53. Alexopoulos, I.; Kounetas, K.; Tzelepis, D. Environmental and Financial Performance. Is there a win-win or a win-loss situation? Evidence from the Greek manufacturing. *J. Clean. Prod.* **2018**, *197*, 1275–1283. [CrossRef]
54. Li, J.J.; Ma, S.C. The Financial Effects of Small and Medium Sized Enterprises Participating in the Bridge Loan Business: Evidence from Companies Listed on SME Board. *J. Financ. Res.* **2017**, *3*, 116–129.
55. An, Y.; Sheng, X.; Zhu, X.; Zhang, Q. The Role of Financial Flexibility in Sustainable Development Performance of SRDI Enterprises. *J. Syst. Sci. Syst. Eng.* **2025**, *34*, 78–101. [CrossRef]
56. Chen, M.; Tan, X.; Zhu, J.; Dong, R.K. Can supply chain digital innovation policy improve the sustainable development performance of manufacturing companies? *Humanit. Soc. Sci. Commun.* **2025**, *12*, 307. [CrossRef]
57. Xi, L.S.; Zhao, H. Senior Executive dual environmental cognition, green innovation and enterprise sustainable development performance. *Bus. Manag. J.* **2022**, *44*, 139–158.
58. La Ferrara, E.; Duryea, S.; Chong, A.E. Soap Operas and Fertility: Evidence from Brazil. *Am. Econ. J. Appl. Econ.* **2012**, *4*, 1–31. [CrossRef]
59. Yao, J.Q.; Zhang, K.P.; Guo, L.P.; Xu, F. How Does Artificial Intelligence Improve Firm Productivity? Based on the Perspective of Labor Skill Structure Adjustment. *J. Manag. World* **2024**, *40*, 101–116.
60. Zhou, C.B.; Zheng, X.S.; Qi, S.Z.; Li, Y.K.; Gao, H.Y. Green credit guideline and enterprise export green-sophistication. *J. Environ. Manag.* **2023**, *336*, 117648. [CrossRef]
61. Knittel, C.R.; Stolper, S. Machine Learning about Treatment Effect Heterogeneity: The Case of Household Energy Use. *AEA Pap. Proc.* **2021**, *111*, 440–444. [CrossRef]
62. Li, B.; Yang, R.; Lu, J.; Jia, Z. Enterprise Digital Transformation, Supply Chain Spillover and Labor Skill Preference. *J. Quant. Technol. Econ.* **2024**, *41*, 133–153.
63. Shang, Y.; Raza, S.A.; Huo, Z.; Shahzad, U.; Zhao, X. Does enterprise digital transformation contribute to the carbon emission reduction? Micro-level evidence from China. *Int. Rev. Econ. Financ.* **2023**, *86*, 1–13. [CrossRef]
64. Wang, S.; Abbas, J.; Sial, M.S.; Álvarez-Otero, S.; Cioca, L.-I. Achieving green innovation and sustainable development goals through green knowledge management: Moderating role of organizational green culture. *J. Innov. Knowl.* **2022**, *7*, 100272. [CrossRef]

65. Yang, X.; Chen, H.; Li, B.; Jia, D.; Ahmad, M. The relationship between artificial intelligence, geopolitical risk, and green growth: Exploring the moderating role of green finance and energy technology. *Technol. Forecast. Soc. Change* **2025**, *217*, 124135. [CrossRef]
66. Wang, G.H.; Nazar, R.; Ali, S.; Meo, M.S. Eco-friendly algorithms: Artificial intelligence and green finance in European intelligent nations. *Technol. Soc.* **2025**, *83*, 102960. [CrossRef]
67. Tao, M.M. Digital brains, green gains: Artificial intelligence's path to sustainable transformation. *J. Environ. Manag.* **2024**, *370*, 122679. [CrossRef]
68. Vasist, P.N.; Krishnan, S. AI's Impact on Sustainability Targets: A Cross-Country NCA and fsQCA Study. *Inf. Syst. Front.* **2024**, *10*, 1–26. [CrossRef]

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