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How Does Artificial Intelligence Impact Green Development? Evidence from China

Mingyue Chen, Shuting Wang and Xiaowen Wang *

School of Economics, Lanzhou University, Lanzhou 730000, China; chenmy2021@lzu.edu.cn (M.C.); shtwang21@lzu.edu.cn (S.W.)
* Correspondence: wxwen@lzu.edu.cn

Abstract: Artificial intelligence not only changes the production methods of traditional industries but also provides an important opportunity to decouple industrial development from environmental degradation and promote green economic growth. In order to further explore the green value of AI, this paper constructs an indicator of industrial robot penetration at the regional level, based on the idea of Bartik's instrumental variable, and measures green development efficiency using the improved Super-SBM model. Based on a comprehensive explanation of the influence mechanism, a spatial measurement model and mediating effect model are constructed to test the spatial spillover effect and transmission mechanism between AI and green development. This study shows that (1) there is a significant inverted U shape in the impact of AI on green development; (2) the heterogeneity analysis finds that the structural dividend of AI is more obvious in capital-intensive and technology-intensive areas, which can more fully release its empowering effect on green development; (3) AI can not only directly affect green development but also indirectly affect green development by promoting green technology innovation and optimizing industrial structures, etc.; (4) AI has a significant inverted U-shaped spatial spillover effect on green development, and the development of local AI has a radiation-driven effect on the green development performance of its spatially related areas. The research methodology of this paper can be used for future research, and the results could provide support for the formulation of regional AI applications and green development policies.

Keywords: artificial intelligence; green development; nonlinearity; spatial spillover; green technological innovation; sustainable development

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1. Introduction

While global economic growth has been rapidly propelled by industrialization and urbanization, it has concurrently resulted in substantial energy inefficiency and environmental degradation issues, thereby fostering an unsustainable trajectory [1]. China, despite attaining remarkable economic success since embracing reform and opening up, grapples with challenges that encompass environmental pollution and inefficient energy usage, given the prevailing notion that industrialization is linked to environmental harm [2]. The Global Environmental Performance Index Report 2022 reveals that China's overall environmental performance positions it 160th out of 180 participating countries and regions. This not only underscores a considerable disparity between China's environmental standing and that of developed nations, but also underscores the pressing need for effective environmental governance. Over an extended period, the primitive model of swift economic expansion and rapid industrialization has led to inefficiencies in energy use, severe environmental pollution, and the degradation of ecosystems. This has, to some extent, hindered the high-quality development of China's economy. Consequently, there is an urgent need for China to foster new drivers for economic development and transition towards an internal model of restructuring the economy and optimizing environmental efficiency. In response to these challenges, promoting a fresh perspective on green development and highlighting the mutually beneficial coordination between economic growth and environmental protection have emerged as crucial approaches [3]. As an embodiment of sustainable development, green economic growth is dedicated to achieving harmony between economic advancement and environmental preservation. The realization of green economic growth has become the prevailing focus of economic development across various nations [4]. This shift is pivotal for addressing the pressing issues associated with China's previous growth model and advancing toward a more sustainable and balanced economic trajectory.

Amidst the advent of the Industry 4.0 revolution, the influence of artificial intelligence (AI), as an emerging technology, on the economy and society has instigated extensive debates [5]. Functioning as a broad technology, numerous scholars have investigated the repercussions of AI on technological advancement and productivity [6]. Within these studies, one perspective posits that AI holds the potential to stimulate technological innovation and augment productivity [7]. Conversely, an alternative viewpoint suggests that AI might give rise to a productivity paradox, negatively impacting productivity growth [8]. Evidently, discourse on the influence of AI on technological innovation and productivity is widespread, yet a consistent conclusion remains elusive. Despite the continuous evolution of new technologies like AI, the global prevalence of severe environmental issues poses a significant challenge to global sustainability. This apparent paradox underscores the need for a balanced perspective. Conversely, inquiries into AI and sustainable development, particularly regarding its capacity to facilitate green development and its spatial variations, remain largely unanswered. This paper endeavors to address and bridge this existing research gap.

This paper makes several noteworthy contributions to the field. Firstly, it employs industry-level robotics data published by the International Federation of Robotics (IFR) spanning 2010–2019. A regional-level industrial robot penetration index is then constructed using the concept of "Bartik instrumental variables". Subsequently, the improved Super-SBM model is applied to gauge the efficiency of green development. In contrast to preceding linear investigations [9], our findings reveal a nonlinear impact of AI on green development, thereby augmenting contemporary discourse on AI development. Secondly, this study delves into the heterogeneous effects of AI, considering differences in capital and technology intensity. This exploration aims to uncover the potential green value of AI. Thirdly, this paper contributes to existing research by examining the influence of green technology innovation and industrial structure upgrading on the relationship between AI and GEG. Unlike prior studies that individually focused on the impacts of digital development on energy [10], the environment [11], and economic growth [12], this research incorporates the crucial role of green technology innovation and industrial structure upgrading into understanding the impact of AI development on GEG. Fourthly, this study investigates the spatial spillover effects of the proposed impact of AI on green development. This examination aids in comprehending the spatial effects of AI externalities on intra- and inter-regional green development. Consequently, it offers a valuable reference for achieving the coordinated growth of regional green economies and further advancing the establishment of a "digital power".

This paper is structured as follows: In Section 2, a brief overview of the literature on AI and GEG is provided. Section 3 offers a detailed presentation of our mechanistic analysis. The methodology and data are outlined in Section 4. Section 5 presents our fundamental empirical results. In Section 6, a mechanism analysis is conducted. The exploration of spatial spillovers is further examined in Section 7. Finally, conclusions and policy implications are established in Section 8 (see Figure 1).

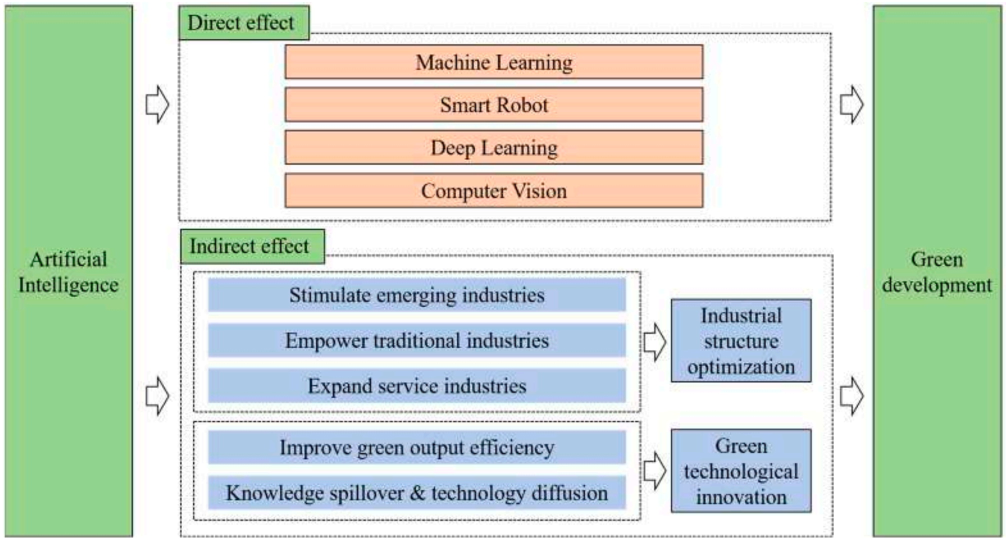


Figure 1. Research framework.

2. Literature Review

2.1. Green Development

Academics have extensively examined and interpreted the meaning, measurement, and influencing factors of GEG from various perspectives ever since its conceptualization [13].

The inception of green development can be traced back to the 1960s, with the emergence of concepts like the circular economy, followed by subsequent notions such as the green economy, ecological economy, low-carbon economy, and sustainable development. In response to the global financial crisis of 2008, scholars began addressing real-world needs by holistically examining the interplay between development and sustainability. This led to the proposition of green development in a new context, encompassing aspects like greening, green growth, green transformation, and green development, imbuing it with fresh significance. The New York University Global Environmental Development Program (NYU-GEDP) delineates "greening" as the transformative process wherein companies reevaluate, cognize, and act upon the ecological environment. Furthermore, in 2008, the UNEP conceptualized a "green economy" as one that not only elevates human well-being and social equity but also mitigates environmental risks and ecological scarcities. Moving forward to 2009, the OECD defined "green development" as a developmental paradigm that ensures sustainable resources and environmental services for human well-being, all the while fostering economic growth.

Total factor productivity (TFP) has long been a prominent subject of research. Presently, faced with the pressures of economic restructuring and upgrading, TFP has garnered extensive attention from the government, the public, and academia [14]. TFP characterizes the magnitude of the growth of "ideal output" propelled by innovation and management, such as technological advancements and enhancements in allocative efficiency. It explicitly excludes tangible factors like labor and capital. Over time, TFP has been widely employed as a measure to assess the quality of economic growth and development [15]. Green TFP, an extension of TFP, includes "undesirable outputs" such as energy and resource inputs and pollution emissions. By accounting for environmental challenges in the process of economic development, it aligns more closely with the contemporary notion of GEG. The measurement methodology for green total factor productivity serves as the cornerstone for studying GEG. In the study of GEG, Pittman [16] was among the first to employ the Data Envelopment Analysis (DEA) method to incorporate undesirable outputs into the TFP measurement framework for estimating Green TFP (GTFP). Chung, et al. [17] expanded on this approach by utilizing DEA and the Malmquist Luenberger (ML) methods to align their outcomes with the concept of GEG. Subsequently, Tone [18] introduced relevant improvements and proposed a more comprehensive Slacks-Based Measure (SBM) model based on non-radial and non-angular slack variables, which effectively reduced computational errors.

With deepening research, the exploration of methods to enhance green total factor productivity (GTFP) has become the focal point of current study. In Particular, the paths and influencing factors for achieving GEG have garnered increasing attention among researchers. Existing research has examined the conditions for GEG with a focus on two categories: economic transformation and environmental factors. Under the framework of economic transformation and upgrading, one line of inquiry argues that factors such as urbanization [19], the digital economy [20], upgrading industrial structures [21], technological innovation, and other determinants [22] facilitate the transformation and upgrading of regional economic structures. These factors optimize the allocation of regional resources, enhance regional economic efficiency, and ultimately foster GEG by improving regional economic efficiency. Another strand of research adopts an environmental protection and pollution reduction perspective. According to the traditional neoclassical school of economics, environmental regulations increase the pollution control costs for businesses, resulting in possible negative effects on their green total factor productivity. However, scholars with a positive outlook argue that sensible environmental regulations can incentivize enterprises to develop green products. These regulations may partially or even entirely offset the augmented costs associated with regulatory compliance and consequently enhance enterprise productivity [23].

2.2. *Artificial Intelligence Applications*

The term "Artificial Intelligence" was initially introduced to academia at the Dartmouth Conference held in the United States in 1956. Since then, it has garnered significant global attention in the 21st century [24]. This concept, often referred to as a "machine capable of human-like thought", has undergone over six decades of advancement, catalyzing progress across diverse industries. The latest generation of AI technology has been integrated to varying degrees within both conventional and emerging sectors, thereby contributing to the stimulation of economic growth.

The existing academic literature on AI can be categorized into two main dimensions: indicator measurement and effects. Regarding indicator measurement, there is a considerable body of academic research dedicated to AI, with distinct indicators employed to measure the level of AI development in quantitative studies. Borland and Coelli [25], for instance, use the "proportion of total societal investment in information transmission, software, and IT services relative to the GDP" as a measure to evaluate AI advancement levels. Meanwhile, other scholars align China's manufacturing industry sectors with the International Federation of Robotics (IFR)'s industry classification for manufacturing. They utilize the installed capacity of industrial robots as an indicator to measure AI [26].

The exploration of the effects of AI is conducted across micro, meso, and macro levels with a comprehensive review of the pertinent literature, such as a study on the impact of AI on microenterprises. In the context of the age of intelligence, the production and operation, transaction distribution, and sales activities of enterprises are increasingly dependent on AI. AI actively contributes to reducing the production costs of enterprises through the realization of "synergy effects" and "efficiency effects". Consequently, this drives a further narrowing of enterprise boundaries [27]. Another notable impact of AI is reflected in the alteration of the organizational structure of enterprises [28]. This transformation involves facilitating the transition towards flattened hierarchical development. As a result, the operational efficiency of enterprises is significantly improved [29]. These advancements in organizational form ultimately foster the high-quality development of enterprises, providing impetus for their growth and overall success. Research on the impact of AI on middle-level industries has garnered considerable attention. With the rapid development of AI, it has become increasingly integrated into first, second, and third industries [30]. The role of AI in enhancing factor productivity has been extensively explored by scholars, and their findings confirm its positive influence. Specifically, some researchers have observed that AI can effectively improve factor productivity, thereby refuting the existence of a "productivity paradox" in regional productivity enhancement [31]. However, it is worth noting that significant variations exist between different regions, as demonstrated by the presence of notable heterogeneity in this regard, as with research on the impact of AI on macroeconomic development. The relationship between information technology and urban economic development has garnered significant attention from scholars, who have devoted considerable efforts towards exploring it both theoretically and empirically [32]. Their findings demonstrate that AI facilitates the re-employment of laborers more effectively than other technologies [33]. Moreover, studies have revealed significant variations in the impact of AI on economic development across different cities. Furthermore, it is evident that the impact of AI on economic development can also differ within the same region over different periods. Notably, there is evidence to suggest a diminishing marginal utility of AI, implying that the incremental benefits obtained from AI implementation may diminish over time [34].

2.3. Artificial Intelligence and Green Development

Research exploring the nexus between AI and green development primarily bifurcates into two distinct realms. Within the first realm, scholars investigate how AI influences total factor productivity (TFP) as a pivotal facet of its impact on green development. Graetz and Michaels [35] underscore TFP as a critical conduit through which intelligence shapes economic expansion. Acemoglu and Restrepo [36] posit that AI holds promise in mitigating demographic challenges, thereby bolstering economic growth via heightened TFP. Contrarily, Yang [37] contends that prevailing AI advancements predominantly elevate TFP within conventional manufacturing sectors, showing its limited influence on TFP within certain advanced manufacturing domains. Nevertheless, the inquiry into AI's ramifications on green total factor productivity (GTFP) and its potential for fostering sustainable economic growth remains nascent. A paucity of research delves into the nuanced mechanisms by which AI systematically impacts GTFP. Transitioning to the second domain, investigations scrutinize AI's ramifications on ecological systems. Within academic discussions, the influence of AI on energy and the environment generates debate. Some scholars posit that AI's application in industries can boost energy efficiency and subsequently reduce related environmental contaminants [38]. Notably, the application of deep learning and big data techniques has been demonstrated to achieve a remarkable energy efficiency improvement of 97.86% [39]. Furthermore, Liu, et al. [40] determined that the utilization of industrial robots yields a marginal carbon reduction effect of 5.44%. Moreover, Zhang and Wu [41], based on an empirical analysis of inter-provincial panel data, drew the conclusion that the application of intelligent technology significantly enhances the green total factor productivity in the manufacturing industry, emphasizing the importance of government attention toward the development of intelligent technology to advance the establishment of a green and low-carbon industry. Contrary to the positive effects of AI on energy conservation, there are also arguments suggesting that AI hinders energy-saving efforts. One significant concern is the substantial energy consumption associated with the repetitive data training required in AI systems [42]. Moreover, the application of AI may improve energy efficiency and reduce the unit cost of energy, but it can lead to a phenomenon referred to as the "rebound effect", wherein firms are incentivized to expand their production, ultimately offsetting the anticipated energy-saving benefits [43]. Studies by Wang, et al. [44], encompassing 38 nations, reveal that industrial robots notably elevate energy intensity. Further, findings from Luan, et al. [45] suggest that such robot usage may exacerbate air pollution and climate shifts, raising environmental concerns.

In summary, previous scholarly investigations have examined the influence of AI on GEG from various angles. However, the existing body of research suffers from insufficient theoretical discourse and empirical validation, necessitating further exploration and the verification of the relationship between AI and GEG. Furthermore, the potential of nonlinear and spatial spillover effects associated with AI has been largely overlooked. Additionally, while many studies have described the correlation between the fundamental aspects of AI and GEG, they have failed to uncover the underlying mechanisms driving this relationship. Consequently, this study aims to build upon the shortcomings identified in previous research and makes two principal contributions to the field. Initially, this study performs an empirical analysis to assert an inverted U-curve connection between AI and sustainable development. It also suggests that the spatial spillover impact of AI exhibits nonlinearity when integrated within the spatial Durbin model. Subsequently, by evaluating the effects of green technology innovation and industrial structure optimization on sustainable development, this study aims to elucidate the direct and ancillary pathways through which AI impacts GEG. This approach not only complements but also augments the current body of knowledge in this domain.

3. Mechanistic Analysis

3.1. Direct Impacts

Currently, there is a limited body of literature that systematically explores the relationship between AI and China's GEG [46]. However, based on economic reasoning and empirical evidence, AI, as a novel technological innovation paradigm, is interconnected with China's GEG in several ways [47]. At the enterprise level, AI facilitates optimal resource allocation, thereby enhancing productivity, cost savings, and sustainable development conditions through the analysis of extensive data, the identification of emerging technological trends, and guidance for investments in green technologies. At the industry chain level, AI's innovative characteristics allow for the clustering and reorganization of innovation elements, leading to synergistic configuration with other factors and expediting the improvement of green technology within the industry chain itself [48]. This improvement not only promotes the application of green technologies but also generates spillover effects that propel the entire industry chain in a greener and more sustainable direction [49]. Intelligent control and monitoring, enabled by AI, lead to improved precision and efficiency in the operation of industrial chains, optimized resource utilization, and reduced energy consumption and pollution. Consequently, these advancements not only yield economic benefits for enterprises but also inject new impetus into the overall GEG of the industry. On an economic level, AI promotes a transition from a resource-driven to a technology- and innovation-driven economic growth model. By optimizing production and supply chain management and enhancing the efficiency and competitiveness of businesses, AI stimulates economic growth [50]. GEG gives rise to new markets and business opportunities, and the application of AI helps companies effectively capitalize on these opportunities. Furthermore, the promotion and application of AI technology contribute to the development of environmental industries, driving employment opportunities and facilitating economic restructuring [11]. GEG represents a vital direction for future economic sustainability, with AI playing a crucial role in achieving sustainable development through technological innovation and market orientation. The application of AI fosters a win–win situation for economic growth and environmental preservation.

Simultaneously, AI could potentially exert adverse effects on green development in its subsequent stages. Numerous AI tasks, particularly those involving deep learning and extensive data processing, necessitate the utilization of high-performance computing devices like graphics processors (GPUs) and large-scale data centers. These devices typically exhibit elevated energy consumption, potentially escalating energy demands and impeding advancements in green development. Swift technological progress and the transience of AI devices might contribute to a substantial accumulation of electronic waste. If not efficiently recycled and disposed of, discarded hardware and electronic components could detrimentally affect the environment. The fundamental trait of AI applications lies in the processing of large-scale data. However, concerns related to personal privacy and data security may arise during data collection, storage, and analysis. The technological prerequisites for safeguarding data privacy and security might increase system intricacy and energy consumption. The widespread integration of AI could induce transformations in traditional industries, thereby influencing the labor market. The decline of specific industries might prompt the workforce to shift towards other sectors, potentially involving energy-intensive start-ups and adversely impacting green development.

3.2. Indirect Impacts

In the current era of widespread AI applications, the challenge lies in harnessing intelligent technology to empower GEG and achieve a harmonious balance between economic and ecological benefits during the development process [51]. While existing research acknowledges the environmentally beneficial effects of intelligent technology, there is a lack of in-depth analysis regarding the pathways and driving mechanisms for realizing the GEG potential of AI [52]. Hence, this paper argues that AI has the potential to unleash the GEG effect primarily through two mechanisms: the empowerment effect of green technology and the optimization effect on industrial structures.

First and foremost, the application of AI enhances enterprises' awareness of and inclination towards adopting green technology [53]. By leveraging AI technology, enterprises can identify and evaluate GEG opportunities with greater accuracy. AI's capacity for efficient information processing facilitates a shift from experience-driven organizations to data-driven entities. This transformation enables organizations to leverage data analysis and forecasting to inform decision making and positively influence the trajectory of green innovation. Consequently, companies are empowered to adopt more sustainable business strategies, mitigate environmental pressures, and foster GEG [54].

Second, the integration of AI technology engenders changes to the traditional industrial structure, ultimately propelling GEG [55]. The introduction and implementation of AI, particularly in areas such as smart manufacturing, smart transportation, and smart cities, have the potential to enhance productivity while diminishing energy consumption and environmental impact [56]. Leveraging the intelligent and automated characteristics of AI, industries with high energy consumption and emissions can be transformed into cleaner, low-carbon forms, thereby optimizing their overall industrial structure [57]. Simultaneously, the advancement of AI has spawned new industries within the green economy, including distributed energy, renewable energy, environmental protection technology, and smart city solutions. The emergence of these sectors offers new employment prospects and fuels the growth of the green economy. AI plays a crucial role in promoting the growth of green industries by optimizing and transforming their industrial structure. It expands the range of choices and possibilities, facilitating the transition towards a more environmentally friendly economy.

3.3. Spatial Spillover Effects of AI on Green Development

There are numerous constraints that impede the exchange of traditional economic information, including factors like geographical distance, sluggish information transmission channels, and limitations associated with time and cost [58]. However, AI disrupts these conventional barriers by enabling cost-effective knowledge and information exchange within shorter timeframes [59]. This facilitates the unrestricted flow of production factors across spatial boundaries, leading to the amplified expansion of capital and technology, along with the enhanced breadth and depth of economic activities across diverse regions [60]. Additionally, the implementation of AI diminishes the constraints imposed by time and space, thereby facilitating the widespread dissemination of clean technology and digital knowledge throughout various regions. This signifies that GEG is no longer confined to localized innovation systems but extends its reach to acquire and learn from the latest green technologies and experiences on a global scale [61]. Consequently, this spatial spillover effect expedites the advancement of green technologies and optimizes resource allocation and industrial structures.

4. Materials and Methods

4.1. Modeling

To conduct a systematic analysis of the influence of AI on GEG, a benchmark model is designed based on the studies by Ren, et al. [62] and Hao, et al. [63].

$$\ln GE_{it} = \alpha_0 + \alpha_1 \ln \mathrm{AI}_{it} + \alpha_2 \ln \mathrm{AI}_{it}^2 + \alpha_3 control_{it} + \lambda_i + \theta_t + \varepsilon_{it} \tag{1}$$

In Equation (1), the explanatory variable $\ln GE_{it}$ represents the GEG level of region i in year t. The main explanatory variable de_{it} is the level of AI application in region i in year t; AI_{it}^2 denotes the squared term of AI, and $control_{it}$ is a series of control variables. In addition, λ_i denotes the region's fixed effects, θ_t denotes fixed time effects, and ε_{it} is the error term.

Further, the previous theoretical analysis suggests that AI changes China's GEG level through innovation drive and structural optimization. In order to identify whether this mechanism exists, this paper constructs the following model:

$$\ln med_{it} = \beta_0 + \beta_1 \ln \mathrm{AI}_{it} + \beta_2 \ln \mathrm{AI}_{it}^2 + \beta_3 control_{it} + \lambda_i + \theta_t + \varepsilon_{it} \tag{2}$$

$$\ln GE_{it} = \gamma_0 + \gamma_1 \ln \mathrm{AI}_{it} + \gamma_2 \ln \mathrm{AI}_{it}^2 + \gamma_3 med_{it} + \gamma_4 control_{it} + \lambda_i + \theta_t + \varepsilon_{it} \tag{3}$$

where lnmed_{it} denotes innovation drive and structural optimization and $control_{it}$ is a set of control variables.

In addition, multiple linear regressions may have a large bias if only general panel data are used. In order to solve this problem, LeSage and Pace [64] is linked to the Durbin model, which is introduced into the standard regression Equation (1) and empirically investigated to establish a spatial Dubin model with double fixed effects, which is constructed as follows:

$$\begin{aligned} \ln GE_{it} = {} & \alpha_0 + \rho_1 \sum_{j=1}^{N} W_{ijt} \ln GE_{it} + \beta_1 \ln GE_{it} + \beta_2 \ln GE_{it}^2 + \beta_3 control_{it} \\ & + \rho_2 \sum_{i \neq j}^{N} W_{ijt} \ln GE_{it} + \rho_3 \sum_{i \neq j}^{N} W_{ijt} \ln GE_{it}^2 \\ & + \rho_4 \sum_{i \neq j}^{N} W_{ijt} control_{it} + \mu_i + \theta_t + \varepsilon_{it} \end{aligned} \tag{4}$$

where W_{ij} is a 31 × 31 spatial weight matrix. This paper adopts two kinds of spatial matrices for testing. First, the impact of AI on GEG is not only limited to neighboring areas; a geographic distance it is close but not adjacent to may also have mutual influence, so a 0–1 spatial adjacency weight matrix is adopted, taking the value of 1 if province i is adjacent to province j, and taking the value of 0 if not [40]. Second, the spatial measurement method is applied to introduce a geographic distance matrix to comprehensively examine the relationship between AI and GEG.

4.2. Variable Selection

4.2.1. Explained Variables

The measurement of GEG levels in the existing literature can be broadly categorized into two main areas: the evaluation of indicator systems and efficiency measurements. Efficiency measurement, in turn, can be further classified into two methods: the stochastic frontier method (SFA) and data envelopment analysis (DEA). Compared to SFA, DEA and its derivative models offer the advantage of evaluating multiple output or input elements simultaneously. However, the traditional DEA model predominantly adopts a radial or angular framework, which disregards the relaxation improvement aspect. In this study, GEG efficiency is assessed using Tone [18] enhanced Super-SBM model, derived from the non-radial and non-angled SBM model. The selected model introduces two significant modifications. Firstly, it eliminates the restriction of equal improvement proportions for each element, enabling adjustments based on the real situation and data characteristics.

Secondly, it relaxes the effective decision-making units (DMUs) ≤ 1 constraint, realizing the comparison of effective DMUs.

Specifically, assuming the existence of n DMUs, each of which can produce s desired outputs y^g and q non-desired outputs y^b, using m types of input factors X, with ρ as the efficiency value, the constructive model takes the following form:

$$\rho = \min \frac{\frac{1}{m}\sum\limits_{i=1}^{m} \frac{\bar{x}_i}{x_{ik}}}{\frac{1}{s+q}\left(\sum\limits_{r=1}^{s} \frac{\bar{y}_r^g}{y_{rk}^g} + \sum\limits_{u=1}^{q} \frac{\bar{y}_u^b}{y_{uk}^b}\right)} \tag{5}$$

$$s.t.\begin{cases} \bar{x} \geq \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j, \ (i = 1, \cdots, m) \\ \bar{y}^g \leq \sum_{j=1,j\neq k}^{n} y_{rj}^g \lambda_j, \ (r = 1, \cdots, s) \\ \bar{y}^b \leq \sum_{j=1,j\neq k}^{n} y_{uj}^b \lambda_j, \ (u = 1, \cdots, q) \\ \bar{x} \geq x_j, \bar{y}^g \leq y_j^g, \bar{y}^b \geq y_j^b \\ \lambda \geq 0, \sum_{j=1,j\neq k}^{n} \lambda_i = 1, \ (j = 1, \cdots, n) \\ s_x^-, s_y^+, s_b^- \geq 0 \end{cases} \tag{6}$$

where s_x^-, s_y^+, s_b^- represent input factors and λ is the weight vector, which, when satisfying the conditions of the constant, returns to scale; $\lambda \geq 0$ and $\sum_{j=1,j\neq k}^{n} \lambda_i = 1$ are the conditions under which the variable returns to scale. Under certain inputs, the larger the desired output and the smaller the non-desired output, the higher the efficiency is, which can be used to measure whether the city can realize high desired output at the cost of lower inputs and less non-desired output, i.e., the GEG efficiency of the city. Specifically, distinct factor inputs include labor inputs, which are represented by the total number of people employed by the end of each year in each region (in tens of thousands); capital factor inputs, which are determined by the depreciation rate computed via the perpetual inventory method and capital stock, with 2009 serving as the reference period; and energy factor inputs, measured in terms of regional electricity consumption (in billion kilowatt-hours). The main indicators of desired output factors include the standard of economic development and the quality of life for residents, with the real gross regional product and the green coverage rate of built-up areas used as proxy variables respective to these indicators. The non-desired outputs, meanwhile, are characterized by sulfur dioxide emissions (in tens of thousands of tons), soot emissions (in tens of thousands of tons), and wastewater emissions (in tens of thousands of tons) per region.

Figure 2 shows the differences in the average value of GEG in different regions. The figure plots the annual average of the level of green development in each region. As can be seen from Figure 2, GEG shows a fluctuating upward trend in all four regions. The eastern region has consistently taken the lead, exhibiting significantly higher levels of development compared to other areas. In contrast, the green development status in the western region lags behind, generally falling below the national average.

4.2.2. Explanatory Variables

This paper uses robot stock data provided by the IFR to characterize *AI* applications. Given that the robot data published by the IFR do not yet contain detailed provincial robot stocks, and that there are large gaps in robot use in different regions, this paper refers to Acemoglu and Restrepo [36] study and applies the Bartik instrumental variables approach to measure robot penetration at the provincial industry level, using the differences in the stock of robots and the differences in the distribution of employment by industry in each province across the starting period.

$$AI_{jht} = \frac{l_{jht_0}}{\sum_{j=1}^{n} l_{jht_0}} \times \frac{AI_{ht}}{l_{ht_0}} \tag{7}$$

AI_{jht} denotes the robot penetration of industry h in province j in year t, $\frac{l_{jht_0}}{\sum_{j=1}^{n} l_{jht_0}}$ denotes the number of people employed in industry h in province j in the base period, and $\frac{AI_{ht}}{l_{ht_0}}$ denotes the robot penetration in industry h in year t.

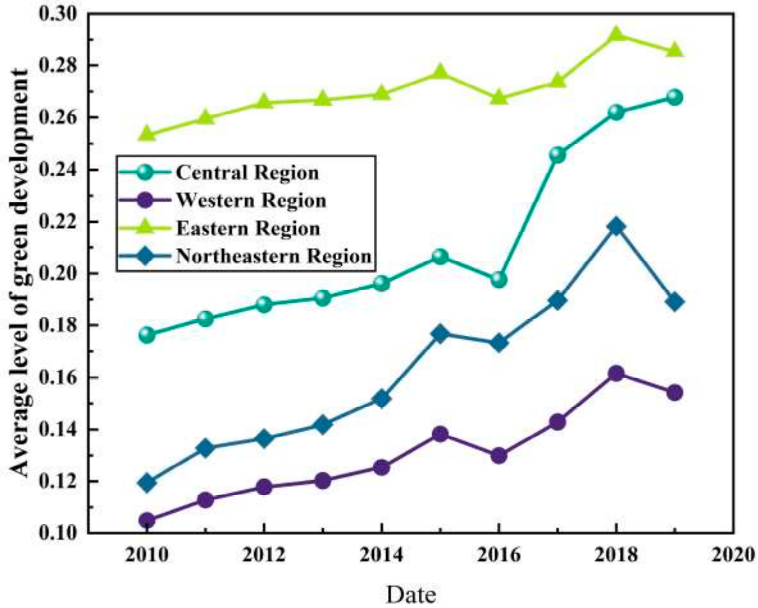
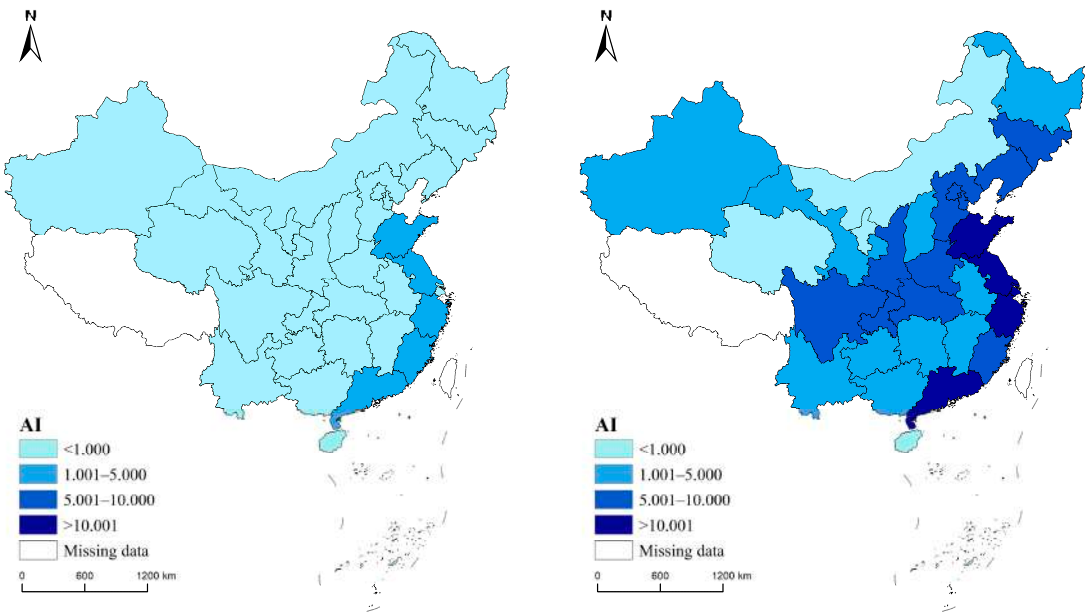


Figure 2. Average change trend of GEG in China's four major regions from 2010 to 2019.

In order to analyze the differences in AI in different years and regions more comprehensively and clearly, this paper applies ArcGIS 2022 mapping software to map the distribution of AI levels in 30 provinces in China in 2010 and 2019, as shown in Figure 3. We found that AI has changed significantly from 2010 to 2019. Overall, the AI levels of 30 provinces in China developed considerably from 2010 to 2019.



(**a**) 2010 (**b**) 2019

Figure 3. Spatial distribution of artificial intelligence in Chinese provinces in 2010 and 2019.

The AI application levels across 30 provinces in the country between 2010 and 2019 were evaluated based on the robot penetration metric computed in the previous section. In order to conduct a comprehensive analysis of the regional disparities in the level of AI application in China, this study employs the division standards provided by the National Bureau of Statistics (NBS) to categorize the measurement samples into the four major economic regions: east, central, west, and northeast. A trend graph, as depicted in Figure 4, is constructed to facilitate a comparative assessment of the sample measurement averages across these regions during the study period. Upon examining the overall trend, it becomes evident that the level of AI application in the country has exhibited an upward trajectory from 2010 to 2019. However, when considering specific regions, it is noteworthy that the eastern region, followed by the east region and the northeast region, witnessed relatively higher rates of increased AI application levels. On the other hand, the western region experienced a slower pace of growth in comparison.

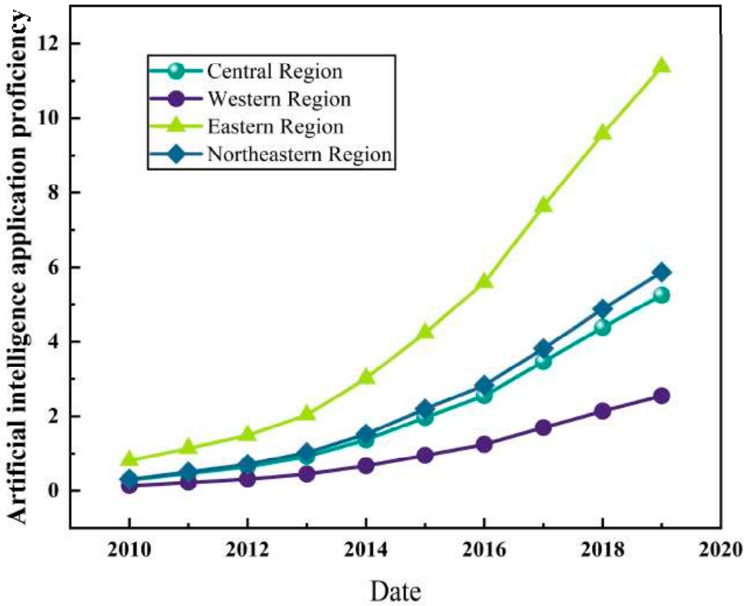


Figure 4. Trends of AI application levels in the four major regions in China, 2010–2019.

4.2.3. Mediating Variables

Green technological innovation: Green technological innovation aligns with the principle of diminishing energy usage and enhancing the environment, thereby offsetting the drawbacks of prior technological advancements that solely prioritized economic gains. Innovations meeting the standards of "eco-friendliness and scientific excellence" are identified as green patents [65]. Green patent applications (GPAs) and green patents authorization (GPG) play a vital role in the realm of green technological innovation [66]. To acquire relevant data on green patent applications and approved patents, this study looked at the International Green Patent Classification (IPC) code, which represents green patents, and accessed the patent database of the State Intellectual Property Office. The data extraction process was based on regional parameters and involved gathering information on the number of green patent applications and the volume of approved green patents, using the filing and approval dates as a reference.

Industrial structure optimization: With the rapid growth of AI in China, significant changes have occurred in the upgrading of domestic industrial structures. To better capture inter-provincial industrial structure optimization in China, this study proposes a refined interpretation of industrial structure upgrading, focusing on two distinct levels: industrial structure advancement and industrial structure rationalization. These levels are established based on a structuralist viewpoint. Based on Wang, et al. [67], advanced industrial structure, denoted as Ais, represents the ratio of value added in tertiary industry to the value added in secondary industry. On the other hand, industrial structure rationalization (Thile) encompasses various aspects such as inter-industry coordination, the quality of industrial structure aggregation, and resource allocation efficiency. The formula used to calculate the industrial structure rationalization index is based on the construction methods suggested by Fan, et al. [68].

$$TL = \sum_{i=1}^{n} \left(\frac{Y_i}{Y}\right) \ln\left(\frac{Y_i}{L_i} / \frac{Y_i}{L}\right) \tag{8}$$

4.2.4. Control Variables

Educational inputs (Edu) denote investments made in the education, training, and practical experience of workers. Edu demonstrates creativity, and augmenting Edu can foster innovation and the adoption of cleaner production technologies, thereby contributing to the advancement of green economic growth [69], which can be measured by examining the proportion of national fiscal expenditure allocated to education within the overall budgetary outlay of local finance in each province.

Marketization (Mark): In general, a higher marketization index signifies a more developed market economy in a given location. This metric refers to the marketization index as evaluated by [68].

Total Import and Export (Trade): Technology diffusion and the inflow of foreign capital have the potential to elevate the level of local green development. The 'Pollution Paradise' hypothesis posits that excessive openness impedes green development due to China's prolonged presence at the lower end of the global value chain, which is quantified by examining the total volume of imports and exports relative to GDP for each province.

Infrastructure Development (Inf): Enhancements in transportation infrastructure yield a dual impact on GEG. On the one hand, improvements can substantially curtail the transportation and transaction costs associated with production factors, fostering the creation of urban economies of scale and industrial agglomeration, thereby leading to an upsurge in GEG. Conversely, infrastructure upgrades might result in increased vehicular traffic, escalating energy consumption and emissions [70]. This scenario could impede GEG. Hence, the influence of transportation infrastructure on GEG requires further empirical scrutiny. Our metric for infrastructure measurement involves urban road space per capita.

Urbanization level (Urb): The acceleration of populations and innovation factor movements across different regions is a notable outcome of urbanization. Concurrently, the population tends to agglomerate, creating favorable conditions for the spillover and dissemination of knowledge, thereby expediting technological innovation [71]. In this research, the chosen indicator for the urbanization level is the proportion of the population residing in urban areas.

Energy structure (Ens): Over the course of almost a century, humanity has extensively consumed energy resources such as coal and oil, resulting in the release of substantial amounts of carbon dioxide and other greenhouse gases. This, in turn, contributes to the phenomenon of global warming [72]. Examined through the percentage of coal consumption in terms of overall energy consumption, energy structure plays a crucial role in understanding environmental impacts and potential mitigation strategies. The Table 1 provides a systematic description of the definitions of each variable.

Table 1. Concrete definitions.

Variable	Definition
Dependent variable	
GEG	Super-SBM model
Core independent variable	
AI	Bartik instrumental variables
Mediating variables	
GPAs	Green patent applications
GPG	Green patents authorization

Table 1. *Cont.*

Variable	Definition
Ais	The ratio of value added in the tertiary industry to the value added in the secondary industry
Thile	Thile model
Control variable	
Edu	The proportion of national education expenditure to local general budget expenditure
Inf	Per capita urban road area
Mark	The marketization index
Urb	The proportion of the population in urban areas
Ens	The proportion of coal consumption to total energy consumption
Trade	The total imports and exports as a proportion of GDP

4.2.5. Data Sources and Descriptive Statistics

This study focuses on an analysis of 30 provincial administrative regions in China spanning the period from 2010 to 2019. The data pertaining to each province have been obtained from the China Statistical Yearbook and the specific statistical yearbooks published for each respective province. In instances where certain data points are missing, an interpolation method had been employed to address the gaps. Table 2 presents the descriptive statistics of each variable.

Table 2. Descriptive statistics.

Variables	N	Mean	Sd	Min	Max
GEG	300	0.269	0.340	0.035	1.491
AI	300	2.611	3.645	0.013	26.650
GPA	300	7.808	1.358	3.434	10.800
GPG	300	7.302	1.377	2.833	10.262
Ais	300	0.033	0.412	−0.694	1.642
Thile	300	−0.800	0.745	−4.075	0.344
Edu	300	−1.822	0.163	−2.313	−1.504
Inf	300	2.673	0.361	1.396	3.266
Mark	300	2.018	0.268	1.212	2.442
Urb	300	4.022	0.208	3.521	4.495
Ens	300	4.244	0.590	0.593	5.265
Trade	300	−1.766	0.951	−4.371	0.460

5. Results

5.1. Basic Regression Results

The initial stage of the analysis involved incorporating AI into both the random effects (RE) and fixed effects (FE) regression models. The findings from these models indicated a positive regression coefficient for the AI variable. To further investigate the possible nonlinearity in the association between AI and GEG, it was deemed essential to incorporate a quadratic term for the AI variable. The outcomes presented in Table 3 revealed positive regression coefficients for AI, while the quadratic terms displayed negative coefficients that passed the 1% significance test. Additionally, both models exhibited significantly higher R^2 values, implying the presence of a substantial inverted U-shaped association between AI and GEG. Following the Hausman test, the FE model was ultimately selected as the preferred model for interpreting the regression outcomes. The regression analysis demonstrated a significant positive relationship between AI and GEG, with a regression coefficient of 0.030. The results imply a noteworthy contribution of AI towards fostering GEG. Additionally, the regression analysis revealed a significant quadratic coefficient of 0.002 for AI, indicating an inverted U-shaped pattern in the influence of AI on GEG. The confirmation of this quadratic relationship was further supported by it passing the 1%

significance test [73]. We find that the inverted U-shaped effect of AI on GEG has been widely explored in existing studies [74,75], implying that the nonlinear nature of the impact of AI is, indeed, not to be ignored.

Table 3. Benchmark regression.

Variable	Re		Fe	
	Linear	**Nonlinear**	**Linear**	**Nonlinear**
AI	0.012 ***	0.054 ***	0.203 ***	0.030 ***
	(0.004)	(0.010)	(0.036)	(0.005)
AI^2		−0.002 ***		−0.002 ***
		(0.000)		(0.000)
Edu	−1.396	−0.564	1.561 **	2.597 **
	(0.834)	(0.824)	(0.728)	(1.236)
Inf	0.022 ***	0.019 ***	0.255 ***	0.125 *
	(0.007)	(0.007)	(0.068)	(0.068)
Mark	0.013	0.055	0.023	0.009
	(0.140)	(0.136)	(0.013)	(0.023)
Urb	−0.010 **	−0.017 ***	−2.617 ***	−0.067 ***
	(0.005)	(0.005)	(0.452)	(0.015)
Ens	−0.550 ***	−0.509 ***	−0.494 ***	−0.002 ***
	(0.045)	(0.044)	(0.039)	(0.000)
Tei	−0.064	−0.068 *	0.054 ***	−0.565
	(0.043)	(0.041)	(0.017)	(0.347)
Cons	0.834 **	0.860 **	9.788 ***	1.047
	(0.347)	(0.335)	(1.709)	(0.721)
Time effect	No	No	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes
Hausman			134.52	64.48
			[0.000]	[0.000]
R^2	0.4872	0.5453	0.6555	0.5454
N	300	300	300	300

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2. Robustness Test

First, concerning the replacement of explanatory variables, the indicators for regional green economy efficiency have been reformulated, replacing the explanatory variables in the initial model. Drawing on the methodologies of Zhang, et al. [76], the weights assigned to both capital and labor inputs in the non-radial direction function have been set to zero, facilitating the assessment of inefficiencies associated with these factors. Furthermore, the energy inputs and desired outputs, namely the actual gross regional product and the greening coverage rate of built-up areas, have been weighted to be 1/3, 1/6, and 1/6, respectively. In contrast, the non-desired outputs, sulfur dioxide industrial outputs, industrial wastewater, industrial emissions of soot and dust, and PM2.5 concentration, have been, respectively, weighted at 1/12 each. These newly defined regional GEG indicators have been integrated into Model (1) for the estimation of model parameters. An examination of Table 4, Column (1) reveals that the primary parameter estimate stands at 0.051 and demonstrates significant positivity, particularly after the substitution of the proxy indicators.

Second, instead of a regression model, this study employs the systematic GMM method. To establish an instrumental variable, the terrain relief is chosen, following the approach utilized by Wang, et al. [39]. Evident in Column (2), AR(1) is less than 0.1, AR(2) is greater than 0.1, and the Sargan test is greater than 0.1, all of which do not reject the null hypothesis, indicating that the instrumental variables in the model are valid. The coefficients present a statistically significant positive relationship at the 5% significance level, thereby reinforcing the robustness of the empirical outcomes.

Table 4. Robustness test.

Variable	(1) GEG	(2) GEG	(3) GEG	(4) GEG
AI	0.159 ***	0.034 **	0.251 ***	0.107 ***
	(0.020)	(0.015)	(0.047)	(0.037)
AI^2	−0.005 ***	−0.023 *	−0.001 ***	−0.006 ***
	(0.001)	(0.013)	(0.000)	(0.002)
cons	−2.305 **		7.381 **	3.112 **
	(1.061)		(3.128)	(1.266)
AR(1)		0.068		
AR(2)		0.244		
Sargan test		0.290		
Controls	Yes		Yes	Yes
Time effect	Yes		Yes	Yes
Individual effect	Yes		Yes	Yes
N	300	300	300	300

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Third, to mitigate the issue of inadequate endogeneity control attributable to the omitted variables, the model is augmented by incorporating Foreign Direct Investment (FDI), the Degree of Financial Development (Df), and population density (Pop) as additional control variables. Subsequent analysis confirms that the initial conclusions maintain their robustness.

Fourth, in order to exclude the interference of outliers, this paper shrinks the 5% data samples before and after the AI variables, and the results are robust, as seen in Table 4, Column (4).

5.3. Heterogeneity

To examine the variations in the impact of AI, further analysis was conducted to classify the sample types. This classification aimed to distinguish differences in the influence of AI based on the average capital intensity and average technology intensity in each region during the sample period. Regions with above-average figures were categorized as capital-intensive and technology-intensive, while those with below-average values were classified as labor-intensive and non-technology-intensive regions. The capital intensity of each region was determined by the average capital stock of employment, while technology intensity was characterized by the percentage of high-tech enterprises. As illustrated in Table 5, the impact of AI on GEG is more pronounced in capital-intensive and technology-intensive regions.

Table 5. Heterogeneity.

Variable	Capital-Intensive Area	Labor-Intensive Area	Technology-Intensive Area	Non-Technology-Intensive Area
AI	1.720 **	0.039 ***	0.999 ***	0.099 ***
	(0.562)	(0.009)	(0.280)	(0.015)
AI^2	−0.001 ***	−0.002 ***	−0.001 ***	−0.008 ***
	(0.000)	(0.000)	(0.000)	(0.002)
Cons	24.774 ***	−0.712 ***	10.681 **	8.011 **
	(5.693)	(0.197)	(3.503)	(3.702)
R^2	0.779	0.515	0.694	0.505
Controls	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes
N	70	230	80	220

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$.

The underlying reasons for this are as follows: Firstly, the substantial capital investment available in capital-intensive regions facilitates research and development efforts and the promotion of AI technology, thereby accelerating the innovation of green technologies. Additionally, these regions typically possesses well-established infrastructure and industrial chains, facilitating the widespread application of AI in energy, transportation, manufacturing, and other sectors, thereby promoting the implementation of GEG initiatives. Additionally, technology-intensive regions can exhibit a high concentration of research institutes, higher education institutions, and high-tech enterprises, fostering a robust capacity for technological innovation. These technology-intensive areas tend to attract specialized technical talents and academic support, which further stimulates the research, development, and application of green technologies. Additionally, the industrial cluster effect observed in technology-intensive regions expedites the replication and diffusion of AI-driven advancements across environmental protection, resource utilization, and other domains, thus facilitating comprehensive progress in GEG.

6. Mechanism Analysis

To further examine the impact of AI on GEG in China, this study builds upon the preceding theoretical analysis and investigates the mechanism through which AI-driven green technological innovation and optimization of the industrial structure contribute to GEG.

Scholarly investigations often focus on evaluating the extent of green technological innovation by primarily considering the number of patent applications or authorizations related to environmentally friendly practices. Recognizing the potential limitations of this single-indicator approach, this study undertakes a comprehensive examination of the mechanisms driving green technological innovation. We introduce two intermediary indicators, namely GPA and GPG, to shed light on the intricate facets of green technological innovation. The findings in columns (1) and (3) reveal a statistically significant impact of AI on green technological innovation at a 1% confidence level. The initial coefficient reveals a significant positive correlation, whereas the subsequent coefficient exhibits a significant negative relationship, indicating an inverted U-shaped association between AI and the advancement of green technological innovation. The outcomes in columns (2) and (4) demonstrate that the coefficients of the number of GPAs and GPG on GEG are 0.056 and 0.133. Consequently, this establishes the mechanism through which AI enhances GEG; via its impact on green technology innovation. Artificial intelligence supports the development of environmentally friendly incentives that allow companies to identify and capitalize on GEG opportunities. Wang, et al. [39] also report that green technology innovations reduce environmental pressures and promote cleaner production through artificial intelligence.

Moreover, the statistical analysis in columns (5) and (7) of Table 6 demonstrates a significant influence of AI on the optimization of industrial structures, with a confidence level of 1%. The first term's coefficient exhibits a significant positive effect, while the second term's coefficient displays a significant negative impact, indicating an inverted U-shaped relationship between AI and industrial structure optimization. The outcomes in columns (6) and (8) reveal that the coefficients of the influence of advanced industrial structure (Ais) and rationalized industrial structure (Thile) on GEG are 0.183 and 0.049, respectively. These coefficients provide additional evidence supporting the mechanism by which AI improves GEG through industrial structure optimization. Nonetheless, an additional discovery by Chen and Wu [75] suggests a substantial enhancement in the environmental performance of manufacturing firms due to artificial intelligence. This implies that AI, as a high-tech industry, might exert a more favorable influence on green development by shaping the internal structure of secondary and tertiary industries.

Table 6. Results of the intermediary effect model.

	(1) GPA	(2) GEG	(3) GPG	(4) GEG	(5) Ais	(6) GEG	(7) Thile	(8) GEG
GPA		0.056 *** (0.014)						
GPG				0.133 *** (0.027)				
Ais						0.183 ** (0.075)		
Thile								0.049 *** (0.016)
AI	0.039 *** (0.004)	0.059 *** (0.005)	0.040 *** (0.003)	0.084 *** (0.007)	0.432 *** (0.106)	0.020 ** (0.008)	0.410 *** (0.040)	0.020 *** (0.005)
AI^2	−0.054 *** (0.005)	−0.002 *** (0.000)	−0.064 *** (0.006)	−0.003 *** (0.000)	−0.000 *** (0.000)	−0.001 *** (0.000)	−0.001 *** (0.000)	−0.001 *** (0.000)
Cons	1.103 (0.677)	5.145 *** (1.302)	2.054 (1.34)	4.837 ** (1.742)	3.108 *** (0.497)	8.333 *** (2.682)	−0.862 (1.543)	−0.166 (0.216)
R^2	0.927	0.563	0.944	0.325	0.856	0.664	0.604	0.503
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	300	300	300	300	300	300	300	300

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$.

In this study, we incorporated green technology innovation, industrial structure optimization, and AI into our model to examine their impact on GEG. As indicated in Table 6, the promotion of GEG is positively influenced by green technology innovation and industrial structure optimization, while AI continues to display an inverted U-shaped effect. Notably, the inflection point at which AI impacts the promotion of GEG is pushed back, implying that green technology innovation and industrial structure optimization serve as partial mediators. In other words, AI indirectly enhances GEG by influencing green technology innovation and industrial structure optimization.

7. Further Study: Space Overflow

To evaluate the spatial spillover effect of AI, we utilized Moran's test. The results presented in Table 7 demonstrate that the global Moran's index exceeds 0. In addition, GEG and AI strongly reject the original hypothesis of no spatial correlation at the 10% and 5% significance levels, respectively. These findings indicate a significant spatial autocorrelation between China's AI and the progress of its GEG, which is characterized by a positive spatial aggregation. Therefore, employing a spatial panel model would be appropriate for further investigation of the spatial spillover effect.

Table 7. Moran index, 2010–2019.

Year	AI			GEG		
	Moran's I	Z-Statistic	*p* Value	Moran's I	Z-Statistic	*p* Value
2010	0.124	1.413	0.079	0.246	2.664	0.004
2011	0.136	1.524	0.064	0.232	2.516	0.006
2012	0.130	1.470	0.071	0.223	2.419	0.008
2013	0.129	1.453	0.073	0.216	2.344	0.010
2014	0.121	1.381	0.084	0.207	2.274	0.011
2015	0.116	1.340	0.090	0.202	2.228	0.013
2016	0.116	1.338	0.091	0.199	2.203	0.014
2017	0.129	1.446	0.074	0.194	2.162	0.015
2018	0.114	1.298	0.097	0.188	2.113	0.017
2019	0.116	1.319	0.094	0.184	2.076	0.019

Given the potential for biases arising from individual differences and time effects, we employed a two-way fixed effects spatial Durbin model (SDM) to estimate the parameters.

Table 8 presents the results, which indicate the following patterns under the two spatial weight matrices: Firstly, sigma2_e significantly indicates that the spatial Durbin model fits the data well. Secondly, the coefficient of AI is positively significant at the 1% level, while the quadratic term associated with AI exhibits a negative coefficient, aligning with the previous empirical findings reported by other researchers. Additionally, the coefficient of Wx is positively significant, whereas the coefficient of Wx2 is negatively significant, both passing the significance test. The results indicate a nonlinear spatial spillover effect of AI on the GEG of adjacent regions, displaying an inverted U-shaped distribution. To gain a deeper understanding of the spatial impact of AI, we disassemble it into two components: the direct effect on local GEG and the indirect effect, reflecting the spatial spillover into neighboring areas. Intriguingly, in both spatial weight matrices, the direct effect, indirect effect, and overall effect all demonstrate inverted U-shaped curves. Consequently, these results demonstrate the stable and sustainable spatial impact of AI on GEG. Expanding the current exploration of AI's influence on energy consumption and sustainability, this discovery aligns with the research conducted by Kopka and Grashof [77]. As per their findings, the efficacy of AI in diminishing energy consumption and fostering sustainability is contingent upon its geographical placement, with a more pronounced effect observed in central areas. The impact of AI on energy consumption decreases as its distance from the center region increases. In contrast, this paper directly examines the spatial impact of AI on green development and concludes that AI can contribute to green development in neighboring cities.

Table 8. Regression results of SDM.

Model		W1		W2	
		Ind	Both	Ind	Both
AI	Main	0.061 ***	0.219 **	0.043 ***	0.288 ***
		(0.011)	(0.098)	(0.012)	(0.099)
	Wx	0.070 ***	0.110 **	0.200 ***	2.795 ***
		(0.023)	(0.051)	(0.059)	(0.677)
	Direct	0.064 ***	0.221 **	0.042 ***	0.239 **
		(0.012)	(0.101)	(0.012)	(0.101)
	Indirect	0.087 ***	0.094 **	0.194 ***	1.960 ***
		(0.025)	(0.045)	(0.052)	(0.575)
	Total	0.150 ***	0.315 ***	0.237 ***	2.199 ***
		(0.031)	(0.103)	(0.058)	(0.593)
AI^2	Main	−0.002 ***	−0.000 ***	−0.002 ***	−0.001 ***
		(0.000)	(0.000)	(0.000)	(0.000)
	Wx	−0.003 ***	−0.001 ***	−0.008 ***	−0.002 **
		(0.001)	(0.000)	(0.002)	(0.001)
	Direct	−0.002 ***	−0.000 ***	−0.002 ***	−0.001 ***
		(0.000)	(0.000)	(0.000)	(0.000)
	Indirect	−0.004 ***	−0.001 **	−0.007 ***	−0.001 *
		(0.001)	(0.000)	(0.002)	(0.000)
	Total	−0.006 ***	−0.001 ***	−0.009 ***	−0.001 **
		(0.001)	(0.000)	(0.002)	(0.001)
Controls		Yes	Yes	Yes	Yes
sigma2_e		0.021 ***	0.012 ***	0.018 ***	0.012 ***
		(0.000)	(0.001)	(0.001)	(0.001)

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

8. Discussion, Conclusions, and Policy Implications

In the context of transitioning economies, AI technology has emerged as a compelling tool for guiding China's economic growth momentum and achieving the mutually beneficial objectives of sustainable development and environmental protection. This study evaluates the level of AI application and its impact on GEG by utilizing panel data spanning 30 provinces in China from 2010 to 2019. The investigation analyzes the nonlinear relationship between AI and GEG through the implementation of a benchmark model, mediating effect model, and the SDM. Additionally, mediation analysis is conducted from the perspectives of green technological innovation and industrial structure optimization. The key findings are summarized as follows: Firstly, our analysis reveals a significant inverted U-shaped relationship between AI and the level of GEG. Secondly, AI is a key factor in the development of a green economy in capital-intensive and technology-intensive areas. Thirdly, AI exhibits both direct and indirect impacts on GEG. The indirect effects are achieved by shaping green technological innovation and optimizing industrial structures. This highlights the importance of AI in influencing and promoting advancements in green technologies and facilitating the restructuring of industries towards environmentally friendly practices. This study reveals a nonlinear spatial spillover effect of AI on the GEG of neighboring cities, exhibiting an inverted U-shaped pattern. In summary, these findings enhance our comprehension of the intricate connection between AI and GEG. They illuminate the potential pathways through which AI technology can facilitate the sustainable transformation of economies, supporting simultaneous economic growth, environmental protection, and sustainable development.

As the largest developing country, China faces the challenge of the simultaneous development of industrialization, urbanization, and environmental protection, and the emergence of artificial intelligence has become a new way for China to balance economic development and environmental protection. The positive effects of AI in promoting green development are observed in this study, but an in-depth analysis of its potential negative effects should not be ignored. First, the inverted U-shaped relationship between AI and GEG suggests that the development of AI to a certain stage may lead to diminishing marginal efficiency or negative impacts on the environment. For example, the operation of AI requires the consumption of a large amount of energy, and in the later stages of development there may be a problem with the excessive construction of data centers and increased energy consumption, leading to increased environmental pressure, especially in areas that rely on non-renewable energy sources, where it may have a more serious impact. Second, labor-intensive and non-technology-intensive regions may see further increases in interregional economic and technological disparities due to AI's lack of a sufficient technological base and capital investment. Finally, the overdevelopment of AI may lead to the accelerated substitution of labor in labor-intensive regions, leading to a decrease in employment opportunities and thus triggering changes in the socioeconomic structure.

In summary, the findings of this study are important for understanding the role of AI in green development and providing a key perspective for the formulation of relevant policies in China and globally. Specifically, the inverted U-shaped relationship between AI and GEG implies that an over-reliance on AI does not bring sustainable benefits to green development and that the government needs to carefully consider the appropriateness and efficiency of AI inputs in designing relevant policies, focusing on the relationship between technological innovation and sustainable development, and strengthening the development of AI at the initial stage, while avoiding the excessive resource consumption and environmental burdens that may be caused by over-investment in AI at the later stage. At the later stage, the excessive resource consumption and environmental burden caused by excessive investment can be avoided. Second, given that AI has a more significant impact on GEG in capital-intensive and technology-intensive zones and a relatively smaller impact in labor-intensive and non-technology-intensive zones, the government should formulate different strategies for the characteristics and needs of different regions when formulating relevant policies. For capital-intensive and technology-intensive zones, the government should continue to encourage and support the research and development of AI and other green-related technologies to further promote the upgrading of industrial structures and to ensure that AI plays the most effective role it can in promoting green development. For labor-intensive and non-technology-intensive areas, infrastructure should be strengthened to promote AI applications suitable for local industries, and corresponding adaptive measures should also be formulated to ensure that the technological transformation does not cause large-scale unemployment in labor-intensive areas. Again, AI has an indirect impact on green development by influencing green technological innovation and industrial structure optimization, implying that the government should accelerate the promotion of eco-friendly industrial upgrading and technological innovation through financial support, tax incentives, and the establishment of cooperative platforms, as well as supporting the transfer and sharing of green technologies on a global scale. Finally, the spatial spillover effects found in this study emphasize the importance of interregional cooperation, which can promote the sharing of new technologies through AI, promote interregional environmental policy coordination, and jointly promote interregional green development. In the global context, the conclusions and policy recommendations of this study provide important references and insights for cooperation between different countries, through AI, to jointly solve transboundary environmental problems.

In response to the conclusions and research limitations drawn from this study, future research can be conducted in the following ways: First, given that there is a spatial spillover effect of the impact of AI on the level of green development, and thus AI may have the potential to enable synergistic cooperation between different regions, future research can start by exploring how AI can promote interregional environmental policy coordination and other aspects of AI, and exploring how interregional environmental policies can be coordinated through AI to carry out cross-regional cooperation to achieve further harmonization of the environment and development among regions. Second, future research could delve into the impact of specific applications of AI within different industries (e.g., renewable energy, green transportation, and low-carbon office sectors) on the promotion of higher levels of green development and assess the environmental footprint of AI applications throughout their life cycles. Finally, future research should more comprehensively consider the multidimensional impact of AI on green development, including issues such as input efficiency, regional development imbalances, and economic and social structural changes, to better understand the important role of AI in sustainable development.

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