

Article

Artificial Intelligence and Urban Green Productivity in China: The Role of Green Computing Capacity and Transmission Channels

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Abstract

Artificial intelligence (AI) is reshaping production systems, innovation processes, and environmental governance, yet its green productivity effects remain ambiguous because AI may both improve efficiency and increase computing-related energy demand. Using panel data for 287 Chinese prefecture-level and above cities from 2005 to 2023, this study examines the relationship between AI technological development and urban green productivity, through which technological transmission channels this effect may operate, and under what boundary conditions it becomes stronger. Green productivity is measured by an undesirable output Super-SBM model, AI by city-level AI patent grants, and green computing capacity by a composite index covering computing infrastructure, green energy support, low-carbon operating efficiency, and computing–network coordination. The results show a robust positive association between AI technological development and urban green productivity, and this conclusion remains robust after alternative measurements, sample restrictions, winsorization, lagged regressors, and Bartik instrumental variable estimations. Green computing capacity is associated with a stronger AI–green productivity relationship. Mechanism-consistent evidence suggests three channels: green knowledge recombination, intelligent regulation of carbon energy flows, and green value-chain coordination. Heterogeneity analyses reveal stronger effects in cities with higher green computing capacity, stronger industrial foundations and weaker resource–environmental constraints. These findings provide city-level evidence for coordinating AI development with green computing infrastructure and low-carbon governance.

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1. Introduction

Accelerating the transition toward cleaner production has become a central task for economies seeking to reconcile economic growth with resource conservation and environmental sustainability. China, as a large industrial economy and one of the world's major energy consumers, faces persistent pressure to improve production efficiency while reducing carbon emissions and pollution. Cities are the key spatial units in this transition. They concentrate industrial production, technological innovation, energy consumption, logistics networks, and environmental governance responsibilities. Whether cities can generate more economic value with fewer resource inputs and lower environmental costs is therefore crucial for achieving high-quality and low-carbon development. Green productivity, measured in this study by green total factor productivity (GTFP), provides an

integrated measure of this process because it incorporates desirable economic output as well as energy inputs and undesirable environmental outputs.

Among the technological forces reshaping cleaner production systems, artificial intelligence (AI) has attracted increasing attention. Compared with conventional digital technologies, AI is not only a tool for information processing but also a general-purpose technology that combines data learning, pattern recognition, prediction, optimization, autonomous decision-making, and knowledge generation [1–3]. These characteristics allow AI to be embedded in production scheduling, equipment operation, energy management, environmental monitoring, logistics optimization, R&D search and supply-chain coordination. In this sense, AI may become an important technological foundation for cleaner production by improving resource allocation, reducing process inefficiency, facilitating green technological innovation, and strengthening low-carbon value-chain coordination.

However, the environmental effect of AI is not straightforward. On the positive side, AI can support cleaner production through predictive maintenance, intelligent process control, energy-load forecasting, smart-grid dispatch, emission monitoring and green product design [4–6]. These applications can help firms and cities increase desirable output while reducing redundant energy consumption, carbon emissions and pollution discharge. On the negative side, AI applications require large-scale data processing, model training, model inference and real-time computing. These activities depend on data centers, intelligent computing facilities, communication networks, and electricity supply. In line with this operations-oriented perspective, this study focuses on the operational-stage negative externalities associated with AI use, computing services, and green productivity measurement, rather than on the environmental impacts generated during the construction stage of data centers or computing facilities. If AI development is supported by carbon-intensive electricity or inefficient computing infrastructure, the additional energy demand may weaken, or even partially offset, its environmental benefits. Therefore, whether AI ultimately improves urban green productivity is not only a question of algorithmic capability or technological adoption, but also a question of whether the underlying computing system is sufficiently green, efficient, and coordinated. This delimitation is important: the empirical framework evaluates operational-stage green productivity and does not constitute a full life-cycle environmental assessment of AI infrastructure. Construction-related embodied carbon, server manufacturing, cooling-water use, electronic waste, land-use pressure, and end-of-life disposal are broader environmental costs that may arise outside the measured city-year production framework.

The existing research has provided important insights into the relationship between digital technologies and green development. Studies on green productivity emphasize the importance of technological progress, environmental regulation, green innovation, and industrial upgrading in improving the efficiency of economic growth under resource and emission constraints [7,8]. A growing literature on digital transformation suggests that data acquisition, intelligent monitoring, digital platforms and supply-chain coordination can promote green innovation, improve energy efficiency and reduce carbon emissions [9–12]. Recent studies have further examined the role of AI in productivity growth, firm innovation, carbon reduction and high-quality development [6,13–15]. At the urban scale, Zhou et al. [16] show that AI-related intelligentization can improve carbon emission efficiency, with industrial upgrading, green innovation networks and energy use efficiency serving as important channels. Recent city-level evidence also shows that AI-driven innovation can improve green total factor productivity through energy efficiency, human capital accumulation and green innovation, and that information infrastructure amplifies this positive effect [17]. Meanwhile, another stream of research warns that AI may generate

environmental costs through higher electricity demand, computing expansion and rebound effects, making its green impact theoretically ambiguous.

Despite these advances, three issues remain insufficiently addressed. First, much of the existing literature treats AI as a subcategory of digital transformation or industrial intelligence, thereby paying limited attention to AI-specific capabilities such as knowledge generation, predictive optimization and autonomous decision-making. Second, existing explanations often rely on broad channels such as green technological innovation, industrial upgrading, or factor allocation, but they rarely clarify how AI reorganizes green knowledge, carbon energy flows, and value-chain relationships within cleaner production systems. Third, although prior studies have emphasized the enabling role of information infrastructure in supporting AI applications and amplifying AI-related green productivity gains, the green attributes of such infrastructure have not been sufficiently examined. The availability of computing infrastructure does not necessarily imply that AI can be scaled in a low-carbon and energy-efficient manner.

To address these gaps, this study investigates the effect of AI on urban green productivity using panel data for 287 Chinese prefecture-level and above cities from 2005 to 2023. It first examines whether AI technological development improves urban green productivity, then explores three transmission channels—green knowledge recombination, intelligent regulation of carbon energy flows, and green value-chain coordination—and finally tests whether green computing capacity strengthens the AI–green productivity relationship across cities with different computing conditions, industrial foundations, and resource–environmental constraints.

This study contributes to the literature in three ways. First, it provides city-level evidence on the role of AI in shaping urban green productivity and clarifies why AI should be distinguished from general digitalization in cleaner production research. Second, it develops and tests three mechanisms linking AI to green productivity, thereby connecting AI with green knowledge recombination, low-carbon process control, and value-chain decarbonization. Third, it introduces green computing capacity as a key boundary condition for AI-enabled green transformation, emphasizing that the environmental effect of AI depends not only on the availability of computing resources, but also on the low-carbon and energy-efficient attributes of the computing system that supports AI applications.

This study therefore defines the three channels more narrowly than the conventional concepts of green innovation, energy efficiency and industrial upgrading. Green knowledge recombination refers to AI-enabled search, matching and recombination among AI and green technology modules; intelligent regulation of carbon energy flows refers to AI-enabled perception, prediction and control of energy use, carbon emissions and pollutant discharge in operational processes; and green value-chain coordination refers to AI-enabled information transparency and coordinated decision-making among manufacturing and producer service actors. These definitions clarify how AI differs from generic digitalization and why green computing capacity is treated as a boundary condition rather than a general urban-development proxy.

In the empirical operationalization, AI is defined as city-level AI technological development and measured by granted AI patents matched to prefecture-level cities; green computing capacity is defined as the ability to support AI training, inference, and industrial intelligentization under cleaner energy, lower carbon intensity, and better computing–network coordination; and the three channels are measured by AI–green integrated patents, carbon energy efficiency indicators and coordinated agglomeration between manufacturing and producer services. These choices link the theoretical concepts to observable city-level indicators while also defining the limits of interpretation.

2. Theoretical Framework and Hypotheses

Green productivity refers to an environmentally compatible form of productivity in which economic output and value creation are improved under resource and emission constraints. Compared with conventional productivity, it not only emphasizes production efficiency but also energy saving, pollution reduction, and low-carbon transformation [7,8]. As a general-purpose technology, artificial intelligence (AI) differs from traditional information technologies because it combines data learning, pattern recognition, prediction, optimization, autonomous decision-making, and knowledge generation [1–3]. These characteristics allow AI to penetrate production, R&D, energy management, environmental governance, and value-chain coordination, thereby reshaping the formation of green productivity.

However, the green effect of AI is not unconditional. AI may improve resource allocation, promote green innovation, optimize production processes, and reduce environmental inefficiency [6,10,13]. At the same time, AI applications rely on data centers, computing infrastructure, and electricity consumption, which may generate additional energy demand and carbon pressure if the supporting infrastructure is not sufficiently green and efficient [5,18]. Moreover, AI and data-center evolution may create broader environmental burdens beyond the industrial CO₂ emissions, wastewater discharge, smoke and dust emissions captured in the GTFP model, such as cooling-water demand, electronic waste, land-use pressure, and embodied emissions associated with infrastructure expansion. Therefore, the net effect of AI on green productivity depends on whether its efficiency-enhancing and low-carbon transformation effects outweigh its potential energy burden. Based on this logic, this study develops a framework consisting of one direct effect, three transmission channels, and one moderating condition.

2.1. Conceptual Scope and Terminology

Several conceptual distinctions are important for interpreting the hypotheses. First, AI technological development refers to the local supply of AI-related technological knowledge, which is measured by AI patent grants in this study. AI adoption refers to the actual use of AI tools, models, equipment, and systems by firms and public agencies, and AI application refers to specific deployment scenarios such as intelligent manufacturing, energy dispatch, environmental monitoring, and supply-chain optimization. Because city-level adoption data are not consistently available for the full sample period, the empirical analysis focuses on AI technological development and interprets the results accordingly. Second, green computing capacity differs from general digital infrastructure. It emphasizes whether computing resources can support AI model training, model inference, and industrial intelligentization under lower energy intensity, cleaner electricity support, and better computing–network coordination. Third, the three transmission channels should be understood as AI-specific operational mechanisms rather than broad labels. Green knowledge recombination is not simply more green innovation; carbon energy flow regulation is not simply higher energy efficiency; and green value-chain coordination is not simply industrial upgrading. Each channel identifies a distinct way in which AI may reorganize cleaner production systems. This conceptual separation also explains why green computing capacity is treated as a complementary asset: AI can generate green productivity gains only when computing resources, cleaner electricity, and network coordination allow AI applications to be deployed without creating excessive additional energy and carbon burdens. The operational definition therefore combines technological capacity with environmental performance rather than treating computing infrastructure as a purely scale-based digital asset.

2.2. Direct Effect of AI on Urban Green Productivity

AI can promote urban green productivity by improving both production efficiency and environmental efficiency. At the firm and process levels, AI can be embedded in equipment operation, production scheduling, logistics management, energy monitoring, and pollution control. Through machine learning, predictive analytics, intelligent sensing, and adaptive control, AI helps firms identify inefficient links, reduce redundant energy consumption, optimize equipment operation, and improve the conversion efficiency of capital, labor, and energy inputs [4,5,19]. These functions are closely related to green productivity because they increase desirable output while reducing energy use and undesirable emissions.

At the city level, AI may also promote green productivity by facilitating industrial upgrading and resource reallocation. As a general-purpose technology, AI changes the relative productivity of firms and sectors, encouraging factors to move from low-efficiency and high-emission activities toward cleaner and higher value-added activities [6,20]. AI-enabled digital transformation may reduce information asymmetry and coordination costs, thereby improving the matching between green technologies, production needs, and environmental constraints [10,21]. In addition, AI may generate a human-enabling effect: by augmenting workers' perception, learning, decision support, and task coordination, AI can help firms improve operational routines, environmental compliance, and low-carbon problem solving rather than merely replacing labor [2,19]. Although AI may bring additional computing-related energy demand, on average, China's policy orientation toward digital transformation and green development suggests that the enabling effect of AI is likely to dominate. Accordingly, this study proposes:

H1. *Artificial intelligence promotes urban green productivity.*

2.3. Green Knowledge Recombination Effect

AI may promote green productivity by strengthening green knowledge recombination. Green technological progress depends not only on R&D investment but also on the search, matching, and recombination of heterogeneous knowledge across technologies, industries, and application scenarios [10,22,23]. Green innovation is often interdisciplinary and scenario-dependent, involving energy technology, environmental governance, materials science, equipment manufacturing, digital technology, and management systems. Therefore, the ability to identify potential technological links and recombine dispersed green knowledge is important for improving urban green productivity.

AI can reduce the search cost and matching cost of green knowledge. Using machine learning, natural language processing, and large-scale data analytics, AI can identify technological links from patents, scientific papers, industrial data, environmental standards, market demand, and policy documents [24–26]. It can also detect complementary relationships among different technological modules, such as intelligent sensing, material optimization, process control, and energy management. In addition, generative AI and intelligent simulation can support new technical solutions, product designs, and process schemes, reducing trial-and-error costs in green R&D [27,28]. Through these mechanisms, AI changes the green knowledge production function and improves the efficiency of green innovation. New green knowledge combinations can generate cleaner technologies and low-carbon production solutions, helping cities move beyond high-energy and high-emission technological lock-in. Accordingly, this study proposes:

H1a. *Artificial intelligence promotes urban green productivity by enhancing green knowledge recombination.*

2.4. Intelligent Regulation of Carbon Energy Flows

AI may also promote green productivity by improving the intelligent regulation of carbon energy flows. Green productivity improvement requires higher desirable output and lower undesirable output under resource and environmental constraints, which is closely related to clean technological change, production process optimization, and environmental performance improvement [29,30]. At the city level, energy consumption, carbon emissions, material inputs, and pollution discharge are jointly embedded in industrial production, transportation, energy supply, and environmental governance systems. These interconnected flows can be understood as carbon energy flows. In traditional production systems, such flows are often difficult to observe, predict, and control in real time, leading to energy waste, inefficient equipment operation, delayed pollution control, and resource-environmental efficiency losses [5,11,31].

AI can improve the perception, prediction, and optimization of carbon energy flows. Intelligent sensors, industrial internet platforms, remote sensing, and online monitoring systems enable AI to transform dispersed information on energy use, equipment status, carbon emissions, and pollutant discharge into identifiable data flows. AI-based prediction models can further anticipate production loads, energy use peaks, equipment failures, and emission trends, improving the forward-looking capacity of production scheduling and environmental governance [4,32]. Through intelligent scheduling, predictive maintenance, digital twins, and process control, AI can dynamically match output targets, energy inputs, and environmental constraints, thereby reducing idle operation, overproduction, ineffective logistics, and excessive use of high-carbon energy. This shifts green transformation from end-of-pipe treatment to process-based prevention and real-time optimization, helping cities approach a low-energy, low-emission, and high-efficiency production frontier. Accordingly, this study proposes:

H1b. *Artificial intelligence promotes urban green productivity by improving the intelligent regulation of carbon energy flows.*

2.5. Green Value-Chain Coordination Effect

AI may further promote green productivity by strengthening green value-chain coordination. The effect of AI is not confined to individual firms. Because AI is highly pervasive, it can cross organizational, industrial, and regional boundaries and reshape value-chain division and coordination [21,33,34]. Green productivity depends not only on local firms' green innovation and energy efficiency but also on whether green technologies, green standards, green products, and green management practices can diffuse along value chains. Production network studies show that shocks, technologies, and organizational changes can propagate through input–output linkages and supply-chain relationships [35,36].

AI can reduce information asymmetry among value-chain participants. In traditional supply chains, firms may find it difficult to obtain timely information on suppliers' environmental performance, product carbon footprints, green technology levels, and downstream green demand. AI can improve the availability, transparency, and matching efficiency of green information through data mining, intelligent identification, and predictive analytics, thereby promoting coordination among green procurement, green production, green logistics, and green sales [4,37,38]. AI-enabled knowledge graphs, intelligent recommendation systems, and collaborative R&D platforms can also facilitate the diffusion of green processes, low-carbon equipment, energy-saving management experience, and environmental standards across firms and industries. Moreover, AI improves demand forecasting, inventory optimization, logistics scheduling, and risk warning, reducing overproduction, ineffective

transportation, and resource waste [5,18]. Therefore, AI can transform firm-level green improvement into value-chain-level green coordination. Accordingly, this study proposes:

H1c. *Artificial intelligence promotes urban green productivity by strengthening green value-chain coordination.*

2.6. Moderating Role of Green Computing Capacity

The green productivity effect of AI depends on complementary infrastructure and resource conditions. AI applications rely on data, algorithms, and computing power. Compared with traditional digital technologies, AI, especially deep learning and generative AI, requires more intensive data processing and computing resources. Therefore, whether the computing system supporting AI is low-carbon, clean, and efficient becomes a key condition for realizing the green benefits of AI [5,18].

Green computing capacity can strengthen the effect of AI on green productivity in two ways. First, it reduces the resource and environmental costs of AI applications. AI-based industrial optimization, energy dispatch, environmental monitoring, and supply-chain coordination require continuous data collection, model training, and real-time computing [4,39]. If local computing infrastructure has low-energy efficiency or relies heavily on fossil-fuel electricity, AI diffusion may increase electricity consumption and carbon emissions, thereby weakening its net contribution to green productivity. In contrast, cities with cleaner electricity supply, more efficient data centers, and better computing–network coordination can support AI applications at lower environmental cost [40,41].

Second, green computing capacity improves the scenario adaptability of AI applications. Stronger green computing capacity enables cities to provide firms with lower-cost, more efficient, and lower-carbon intelligent computing services, reducing the threshold for AI-based green transformation. It also reinforces the three mechanisms discussed above by expanding the capacity for green knowledge search and simulation, improving the real-time regulation of carbon energy flows, and facilitating data connection and collaborative decision-making across value chains. Therefore, green computing capacity constitutes an important boundary condition for transforming AI capabilities into green productivity gains. Accordingly, this study proposes:

H2. *Green computing capacity positively moderates the relationship between artificial intelligence and urban green productivity; that is, the stronger a city's green computing capacity, the greater the positive effect of artificial intelligence on urban green productivity.*

3. Materials and Methods

3.1. Empirical Specification

To estimate the average effect of AI on urban green productivity, this study employs a two-way fixed-effects model that controls for time-invariant city characteristics and common yearly shocks:

$$GTFP_{it} = \alpha_0 + \alpha_1 AI_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where i and t denote city and year, respectively. $GTFP$ denotes green total factor productivity, which is used to proxy urban green productivity; AI denotes city-level AI technological development; X_{it} is a vector of control variables; μ_i and λ_t are city and year fixed effects; and ε_{it} is the error term. Standard errors are clustered at the city level.

To test the moderating effect of green computing capacity, we further estimate:

$$GTFP_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 GCC_{it} + \beta_3 (AI_{it} \times GCC_{it}) + \theta' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where *GCC* denotes green computing capacity. A positive and significant β_3 indicates that green computing capacity strengthens the effect of AI on green productivity.

The two-way fixed-effects model reduces bias from time-invariant city characteristics and common year shocks, but it cannot fully remove time-varying omitted variables. Therefore, the empirical analysis combines lagged regressors, alternative measurements, sample restrictions, and a Bartik shift-share instrumental variable. The IV results are interpreted as supplementary evidence rather than as a complete solution to all endogeneity concerns, because the initial AI base may be correlated with long-term innovation capacity, human capital, industrial structure and infrastructure quality. To mitigate this concern, the regressions control for economic development, education, internet penetration, foreign investment and science and technology expenditure, and the validity of the instrument is discussed explicitly in the endogeneity section. Accordingly, the estimated coefficients are interpreted as robust conditional associations with an IV-supported identification strategy, not as definitive proof that all reverse causality and omitted-variable concerns have been eliminated.

3.2. Variable Construction

Green productivity. We proxy green productivity by green total factor productivity (GTFP). Following Tone [42] and related undesirable output DEA studies [43,44], we estimate city-level GTFP using an undesirable output Super-SBM model, which accounts for input–output slacks and allows efficient decision-making units to be further ranked. This model stems from the data envelopment analysis (DEA) literature, which constructs a relative efficiency frontier from observed decision-making units without imposing a parametric production function. The Super-SBM specification is suitable for this study because it is non-radial and non-oriented, treats undesirable outputs explicitly, captures input redundancy and undesirable output excesses, and can distinguish cities located on the efficient frontier. In the benchmark measurement, cities are treated as decision-making units, the model is estimated under variable returns to scale, and annual frontiers are constructed to reduce the influence of intertemporal changes in production technology. Inputs include capital stock estimated using the perpetual inventory method with 2005 as the base year, labor measured by the number of urban employees, and energy consumption converted into standard coal equivalents. The desirable output is real GDP at constant 2005 prices, while undesirable outputs include industrial CO₂ emissions, industrial wastewater discharge, and industrial smoke and dust emissions. A higher GTFP value indicates stronger urban green productivity. Details on the model specification and input–output indicator system are reported in Appendix A. Industrial CO₂ emissions are estimated from city-level energy consumption and standard emission coefficients where directly reported city-level CO₂ data are unavailable; environmental indicators are checked against official statistical yearbooks, and interpolation is used only for short missing segments with internally consistent adjacent observations.

Artificial intelligence. The core explanatory variable is city-level AI technological development, proxied by the number of granted AI patents [14,44]. This proxy captures the supply-side innovation capacity of AI rather than the full scope of AI adoption. AI patents are identified according to the artificial intelligence categories in the Key Digital Technology Patent Classification System (2023) issued by the China National Intellectual Property Administration [45]. Patent grants are preferred because they better reflect validated and implementable technological outputs than patent applications and reduce potential noise from repeated, withdrawn, or low-quality applications. Compared with alternative measures such as robot density, AI financing, and composite indices, granted AI patents cover a broader range of algorithmic, hardware, and application-oriented innovations and

are consistently available across cities and years [33,46,47]. Patent records are matched to cities according to applicant addresses and prefecture-level administrative codes. City names and boundary changes are harmonized before aggregation, duplicated grants are removed, and zero-patent observations are retained because a zero-patent count remains zero after scaling. This scaling treatment avoids dropping late-developing cities and allows the coefficient to be interpreted as the association between changes in AI patent grants measured in units of 10,000 and green productivity. This paper also distinguishes AI invention from AI diffusion and AI application: AI patents mainly capture invention-side technological supply, while AI firms are used as an alternative measure in the robustness checks where comparable city-level data are available. Other indicators, such as patent applications, robot deployment and direct AI-adoption measures, are useful extensions for future research. Therefore, the empirical results should be understood as evidence on AI-related technological development at the city level, not as a direct measurement of the intensity, quality, or sectoral breadth of AI adoption in firms and public agencies.

Green computing capacity. Green computing capacity reflects a city's ability to support AI model training, model inference, and industrial intelligentization in a green, low-carbon, and efficient manner. Following official policy documents and industry reports on green data centers and high-quality computing infrastructure [48–50], this study constructs a green computing capacity index from four dimensions: computing infrastructure capacity, green energy support, low-carbon operating efficiency, and computing–network coordination and utilization. Computing infrastructure capacity captures the supply of data centers, intelligent computing resources, and digital infrastructure; green energy support reflects renewable energy availability and green electricity consumption; low-carbon operating efficiency captures the energy efficiency and carbon constraints of computing facilities; and computing–network coordination and utilization reflects computing resource scheduling, network transmission, and resource-use efficiency. After standardizing the indicators, the entropy-weighting method is used to calculate the city-level green computing capacity index. The entropy-weighting method is selected because it assigns weights according to the amount of information and cross-city variation contained in each indicator, thereby reducing subjective weighting bias and improving comparability across indicators with different units and scales. This approach is particularly appropriate for a composite index such as green computing capacity, where the four dimensions capture heterogeneous but complementary infrastructure, energy and efficiency conditions. For transparency, Appendix B reports the variable dictionary, the indicator structure, data-source categories and the reconstruction procedure for this index. Positive indicators are standardized as $x' = (x - \min) / (\max - \min)$, while negative indicators are standardized as $x' = (\max - x) / (\max - \min)$. Entropy values, information utility values, and final weights are then calculated using the standardized city-year panel. Missing values are treated in the same way as other city-level indicators: short and internally consistent gaps are interpolated, while observations with severe discontinuity are excluded. Appendix C describes additional robustness procedures based on equal weighting and PCA-based weighting, so as to examine whether the moderating effect of GCC is robust to alternative weighting schemes. The index is designed to capture operational green computing conditions observable at the city level; it does not fully measure embodied emissions from construction and equipment manufacturing or environmental impacts from hardware disposal. Because the renewable energy support indicator is constructed from provincial renewable-power conditions and then matched to prefecture-level cities, the GCC index partly captures regional clean-energy support conditions in addition to city-level computing and network infrastructure. Accordingly, GCC should be interpreted as an operational green computing environment that combines computing availability, cleaner electricity support, low-carbon

operating efficiency, and computing–network coordination, rather than as a pure city-level data-center capacity measure.

Mechanism variables. To test the transmission channels, this study constructs three mechanism variables. Green knowledge recombination is proxied by the number of AI–green integrated patents, following patent-based measures of technological innovation and knowledge recombination [51–53]. AI–green integrated patents are identified from the intersection between AI patent classifications and green patent taxonomies, such as the WIPO IPC Green Inventory, CPC-Y02/Y04S, or OECD environmental technology classifications. To improve classification reliability, patent records were cleaned by removing duplicated grants, harmonizing city names and administrative boundary changes, matching applicant addresses to prefecture-level cities, and cross-checking AI and green patent labels against the CNIPA AI classification and international green patent taxonomies. Ambiguous records were manually inspected through titles, abstracts, and IPC/CPC codes before inclusion. Carbon energy flow regulation is measured by an entropy-weighted index based on energy and carbon-use efficiency indicators, including energy consumption per unit of GDP, electricity consumption per unit of GDP, carbon emissions per unit of GDP, carbon productivity, and electricity output efficiency. Negative indicators are reverse-standardized before index construction. Green value-chain coordination is proxied by the coordinated agglomeration of manufacturing and producer services, following studies on production networks, supply-chain propagation, and resource reallocation [20,35,36]. This variable captures the degree of integration between manufacturing production and producer service functions along value chains. These variables are used to provide mechanism-consistent evidence rather than formal causal mediation. Green knowledge recombination may partly overlap with the AI patent measure, carbon energy flow regulation is conceptually close to the resource and emission dimensions of GTFP, and coordinated agglomeration may also reflect broader industrial structure. These limitations are explicitly discussed when interpreting the results.

Control variables. Following related studies [44,54,55], we include a set of city-level control variables. Foreign investment activity (*fdi*) is measured by the number of foreign-invested enterprises; education level (*edu*) is measured by the number of students enrolled in regular higher-education institutions; economic development (*GDP*) is measured by GDP per capita; urbanization (*urb*) is measured by the share of the urban population in total population; internet penetration (*net*) is measured by broadband users per 100 persons; and science and technology support (*sci*) is measured by government science and technology expenditure as a share of real GDP.

3.3. Data Sources and Sample

The sample covers 287 prefecture-level and above Chinese cities from 2005 to 2023. Cities with severe data limitations are excluded. Tibet is excluded because city-level energy and environmental statistics required for the undesirable output GTFP measurement are highly discontinuous over the sample period. Hong Kong, Macao and Taiwan are not included because their statistical systems, patent records and urban administrative units are not directly comparable with those of mainland prefecture-level cities. The data are drawn from the China Statistical Yearbook, China City Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, the China National Intellectual Property Administration, the National Bureau of Statistics, and the CSMAR database. Monetary variables are deflated to constant prices, and missing observations are treated using interpolation when appropriate. Appendix B reports the variable dictionary, data-source table and indicator construction procedure to improve reproducibility. The assembled dataset and code can be made available from the corresponding author upon

reasonable request, subject to the redistribution restrictions of the original statistical and patent databases.

4. Results

4.1. Baseline Regression and Moderating Effect

Table 1 reports the baseline regression results. Columns (1)–(5) progressively add controls and fixed effects. Across specifications, the coefficient of AI remains positive and statistically significant at the 1% level. In the preferred two-way fixed-effects specification with controls in column (5), the coefficient of AI is 0.048 and significant at the 1% level, indicating a robust positive AI–green productivity relationship. In terms of economic magnitude, a one-standard deviation increase in AI is associated with an increase of 0.024 in the GTFP index, equivalent to approximately 7.67% of the sample mean of GTFP. Column (6) adds green computing capacity and the interaction term between AI and green computing capacity. The coefficient of AI remains positive and significant, and the interaction term is significantly positive. To make the moderating effect more transparent, using the coefficient estimates in column (6), the marginal association of AI with GTFP can be written as $\partial \text{GTFP} / \partial \text{AI} = 0.024 + 0.007 \times \text{GCC}$. At a low GCC level, defined as the mean minus one standard deviation and truncated at the sample minimum of 0, the marginal association is 0.0240; at the sample mean of GCC (0.095), it is 0.0247; and at a high GCC level, defined as one standard deviation above the mean (0.195), it rises to 0.0254. Although the numerical difference is modest because GCC is normalized to the [0, 1] interval, the pattern indicates that the positive AI–GTFP relationship becomes stronger when green computing conditions improve. These results are consistent with H1 and H2: AI technological development is positively associated with green productivity, and green computing capacity strengthens this relationship.

Table 1. Baseline estimates of the AI–green productivity relationship and moderating effect of green computing capacity.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.074 *** (0.004)	0.042 *** (0.004)	0.041 *** (0.004)	0.048 *** (0.004)	0.048 *** (0.004)	0.024 *** (0.002)
GCC						0.001 (0.002)
AI * GCC						0.007 *** (0.001)
fdi		0.004 (0.006)	−0.062 *** (0.015)	0.027 *** (0.006)	−0.077 *** (0.014)	−0.081 *** (0.014)
edu		0.003 ** (0.001)	0.033 *** (0.003)	0.003 *** (0.001)	0.027 *** (0.003)	0.023 *** (0.003)
GDP		0.128 *** (0.006)	0.150 *** (0.006)	0.092 *** (0.007)	0.079 *** (0.008)	0.078 *** (0.008)
urb		0.004 (0.012)	−0.021 * (0.011)	0.003 (0.012)	−0.063 *** (0.012)	−0.062 *** (0.011)
net		0.008 *** (0.001)	0.003 *** (0.001)	0.005 *** (0.001)	−0.002 (0.001)	−0.002 (0.001)
sci		−0.319 *** (0.087)	0.028 (0.073)	−0.516 *** (0.091)	−0.277 *** (0.079)	−0.372 *** (0.080)
_cons	0.308 *** (0.001)	0.244 *** (0.005)	0.228 *** (0.005)	0.267 *** (0.005)	0.301 *** (0.007)	0.311 *** (0.007)

Table 1. Cont.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
City	Yes	No	Yes	No	Yes	Yes
Time	Yes	No	No	Yes	Yes	Yes
N	5453	5453	5453	5453	5453	5453
R ²	0.716	0.233	0.347	0.146	0.731	0.733

Notes: Robust standard errors clustered at the city level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. GCC denotes green computing capacity.

4.2. Robustness Tests

To evaluate the reliability of the baseline findings, this study conducts robustness checks by replacing the dependent variable, replacing the core explanatory variable, excluding selected samples, adjusting the sample period, and winsorizing the variables. Table 2 shows that the AI coefficient remains positive and significant across all checks. Specifically, results remain robust when green productivity is remeasured by a super-efficiency CCR model, AI is proxied by the number of AI firms, municipalities are excluded, a restricted sample of large and innovation-oriented cities is used, the sample period is adjusted to 2013–2021, and key variables are winsorized at the 1% level. These robustness checks reduce concerns that the baseline result is driven by a particular measurement of green productivity, the patent-based AI proxy, sample composition, the sample period, or extreme values. Appendix C reports descriptive statistics, correlation analysis, and variance inflation diagnostics for the main variables, and further summarizes additional robustness checks based on alternative GCC constructions where comparable city-level data are available.

Table 2. Robustness tests using alternative measurements and sample adjustments.

Variable	(1) CCR	(2) AI Firms	(3) Excl. Municipalities	(4) Restricted Cities	(5) 2013–2021	(6) Winsorized
AI	0.034 *** (0.005)		0.059 *** (0.006)	0.043 *** (0.005)	0.050 *** (0.007)	0.045 *** (0.011)
AI firms		0.035 *** (0.003)				
fdi	−0.108 *** (0.018)	−0.093 *** (0.014)	−0.137 *** (0.019)	−0.068 *** (0.020)	−0.197 *** (0.051)	−0.111 *** (0.014)
edu	0.036 *** (0.003)	0.021 *** (0.003)	0.027 *** (0.003)	0.028 *** (0.004)	0.038 *** (0.006)	0.026 *** (0.003)
GDP	0.084 *** (0.010)	0.085 *** (0.008)	0.077 *** (0.008)	0.114 *** (0.020)	0.109 *** (0.015)	0.092 *** (0.008)
urb	−0.073 *** (0.015)	−0.069 *** (0.012)	−0.065 *** (0.012)	−0.046 (0.029)	−0.063 *** (0.021)	−0.074 *** (0.011)
net	0.001 (0.001)	−0.003 ** (0.001)	−0.002 ** (0.001)	−0.008 *** (0.002)	−0.002 (0.002)	−0.003 ** (0.001)
sci	−0.228 ** (0.102)	−0.133 * (0.079)	−0.268 *** (0.081)	0.009 (0.169)	−0.430 *** (0.132)	−0.233 *** (0.078)
_cons	0.522 *** (0.009)	0.309 *** (0.007)	0.309 *** (0.007)	0.305 *** (0.024)	0.306 *** (0.016)	0.307 *** (0.007)
City	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
N	5453	5453	5377	1197	2583	5453
R ²	0.736	0.729	0.728	0.713	0.773	0.733

Notes: Robust standard errors clustered at the city level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.3. Endogeneity Tests

Potential endogeneity may arise from reverse causality between AI and green productivity, or from omitted variables. This study addresses these concerns using lagged explanatory variables and a Bartik shift-share instrumental variable. The results of these endogeneity tests are reported in Table 3. The Bartik instrument is constructed from each city's initial AI base in 2005 and the national growth of AI technologies excluding the city itself. The first-stage results indicate that the instrument is strongly correlated with AI, and the Kleibergen–Paap LM statistic rejects under-identification. The second-stage results remain significantly positive, suggesting that the baseline conclusion is not driven primarily by reverse causality or simultaneity bias. The exclusion restriction is not assumed mechanically. The rationale is that the interaction between the initial AI base and national AI growth mainly shifts local AI technological development through exposure to a common technological trend, while city and year fixed effects and controls absorb persistent local characteristics and common shocks. Nevertheless, because the initial AI base may still be correlated with unobserved long-run innovation trajectories, the IV estimates are interpreted cautiously as robustness evidence. The larger IV coefficients may reflect local average treatment effects for cities whose AI development is more strongly affected by national AI expansion, measurement error in the patent-based AI proxy, or remaining differences between OLS and IV identifying variation. These qualifications are important because cities with stronger AI bases may also possess unobserved policy capacity, firm capabilities, or environmental management institutions that are difficult to fully measure. The endogeneity tests therefore strengthen the credibility of the baseline relationship but do not remove the need for cautious interpretation.

Table 3. Endogeneity tests using lagged regressors and the Bartik instrumental variable.

Variable	(1) Lagged Variables	(2) Lagged Variables	(3) Bartik IV	(4) Bartik IV
AI	0.077 *** (0.004)	0.053 *** (0.004)	1.043 *** (0.247)	0.946 *** (0.299)
fdi		−0.083 *** (0.015)		−0.024 (0.037)
edu		0.032 *** (0.003)		0.021 *** (0.005)
GDP		0.074 *** (0.008)		0.061 *** (0.014)
urb		−0.059 *** (0.014)		−0.050 *** (0.015)
net		−0.004 *** (0.001)		−0.001 (0.001)
sci		−0.301 *** (0.086)		−0.370 *** (0.099)
_cons	0.315 *** (0.001)	0.311 *** (0.008)		
City	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
N	5166	5166	5453	5453
R ²	0.717	0.731	0.323	0.348
First-stage F			135.180	129.136
Kleibergen–Paap LM				90.725 ***

Notes: Robust standard errors clustered at the city level are reported in parentheses. *** indicate significance at the 1% level.

4.4. Further Analysis

4.4.1. Mechanism Tests

This study further examines the proposed transmission channels. Table 4 reports the mechanism-consistent tests for the three AI-related transmission channels. The results show that AI is significantly associated with improvements in green knowledge recombination, carbon energy flow regulation, and green value-chain coordination. These findings provide evidence consistent with the three mechanism pathways proposed in the theoretical framework. Specifically, AI may promote green productivity not only by increasing green technological outputs, but also by changing knowledge-search and matching processes, improving the real-time management of energy use and emissions, and strengthening green coordination across value chains. Because the mechanism variables are not randomly assigned and may overlap conceptually with AI innovation or green productivity, these estimates should not be interpreted as definitive causal mediation. They indicate whether the observed AI–green productivity relationship is consistent with the proposed channels. In this sense, the mechanism analysis is intended to test whether the proposed theoretical channels are empirically plausible, rather than to decompose the baseline effect into confirmed causal mediation shares.

Table 4. Mechanism-consistent tests for AI-related transmission channels.

Variable	(1) GKR	(2) GKR	(3) CEFR	(4) CEFR	(5) GVCC	(6) GVCC
AI	0.012 *** (0.000)	0.009 *** (0.000)	0.003 *** (0.000)	0.001 *** (0.001)	0.001 *** (0.000)	0.002 *** (0.000)
fdi		−0.010 *** (0.001)		−0.002 (0.002)		−0.001 *** (0.000)
edu		0.002 *** (0.000)		0.000 (0.000)		0.000 *** (0.000)
GDP		0.002 *** (0.000)		0.007 *** (0.001)		−0.003 *** (0.000)
urb		−0.001 *** (0.000)		−0.013 *** (0.001)		−0.000 (0.000)
net		0.000 *** (0.000)		0.000 (0.000)		−0.000 (0.000)
sci		0.058 *** (0.003)		−0.027 *** (0.010)		0.001 (0.003)
_cons	0.002 *** (0.000)	−0.001 *** (0.000)	0.441 *** (0.000)	0.445 *** (0.001)	0.010 *** (0.000)	0.011 *** (0.000)
City	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
N	5453	5453	5453	5453	5453	5453
R ²	0.819	0.854	0.887	0.889	0.822	0.828

Notes: GKR denotes green knowledge recombination; CEFR denotes carbon energy flow regulation; GVCC denotes green value-chain coordination. Robust standard errors clustered at the city level are reported in parentheses. *** indicate significance at the 1% level.

4.4.2. Heterogeneity Analysis

Because cities differ in computing conditions, industrial foundations, and resource-environmental constraints, the effect of AI is unlikely to be homogeneous. Table 5 reports subgroup estimates. The coefficient of AI is larger and significant in cities with high green computing capacity, indicating that low-carbon computing infrastructure provides the complementary condition required for AI-enabled green productivity growth. The effect is also stronger in cities with a solid industrial base, suggesting that AI needs sufficient manufacturing scenarios and absorptive capacity to generate green productivity gains. Finally, the effect is more pronounced in cities with weaker resource-environmental constraints.

This result should not be interpreted as suggesting that resource-environmental constraints should be weakened. Rather, it indicates that cities under stronger constraints often face higher legacy costs, high-carbon path dependence and adjustment frictions, which may slow the short-run conversion of AI into green productivity unless AI deployment is combined with cleaner energy use, industrial retrofitting and stricter low-carbon governance. The groups are divided according to the sample median of the corresponding city-level indicator unless otherwise specified. The negative coefficient in cities with weak industrial foundations is interpreted as evidence that AI may fail to generate green productivity gains when absorptive capacity, manufacturing scenarios and complementary organizational routines are insufficient.

Table 5. Heterogeneity analysis across green computing capacity, industrial foundations and resource-environmental constraints.

Variable	(1) Low GCC	(2) High GCC	(3) Weak Industrial Base	(4) Strong Industrial Base	(5) High Constraints	(6) Low Constraints
AI	0.017 (0.019)	0.046 *** (0.005)	−0.176 * (0.098)	0.045 *** (0.005)	0.018 (0.016)	0.051 *** (0.005)
fdi	0.003 (0.022)	−0.074 *** (0.020)	0.063 ** (0.026)	−0.086 *** (0.019)	−0.087 *** (0.021)	−0.079 *** (0.020)
edu	0.004 (0.006)	0.028 *** (0.004)	−0.010 (0.011)	0.026 *** (0.003)	0.014 *** (0.005)	0.034 *** (0.004)
GDP	0.078 *** (0.011)	0.070 *** (0.012)	0.072 *** (0.008)	0.086 *** (0.014)	0.081 *** (0.010)	0.079 *** (0.012)
urb	−0.078 *** (0.018)	−0.058 *** (0.015)	−0.104 *** (0.013)	−0.042 ** (0.018)	−0.102 *** (0.013)	−0.013 (0.019)
net	0.001 (0.002)	0.001 (0.001)	−0.001 (0.002)	−0.002 (0.002)	0.000 (0.001)	−0.003 * (0.002)
sci	−0.211 (0.132)	−0.192 * (0.108)	−0.233 * (0.130)	−0.379 *** (0.113)	−0.177 * (0.106)	−0.268 ** (0.116)
_cons	0.307 *** (0.010)	0.298 *** (0.011)	0.314 *** (0.007)	0.307 *** (0.013)	0.308 *** (0.008)	0.284 *** (0.012)
City	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
N	2726	2726	2717	2724	2736	2717
R ²	0.742	0.794	0.810	0.751	0.741	0.718

Notes: GCC denotes green computing capacity. Robust standard errors clustered at the city level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Coefficient-difference tests show the following pairwise differences: High GCC–Low GCC = 0.029 **; Strong industrial base–Weak industrial base = 0.220 ***; Low constraints–High constraints = 0.033 ***.

5. Discussion

5.1. Net Effect of AI and the Green Computing Boundary

The empirical evidence indicates a positive net relationship between AI and urban green productivity. This finding contributes to the debate on whether AI acts as an accelerator of low-carbon transformation or as a new source of energy demand. It should not be interpreted as evidence that computing-related energy consumption is negligible. Rather, it suggests that, on average, the productivity-enhancing effects associated with green knowledge recombination, intelligent regulation of carbon energy flows, and green value-chain coordination dominate potential computing-related energy burdens in terms of green productivity. It also does not imply that AI automatically causes green transformation in every city or sector. The net effect depends on actual adoption intensity, industrial application scenarios, electricity structure, data-center efficiency, governance capacity, and the environmental cost of supporting infrastructure. Nor should it be read as a full en-

vironmental accounting of AI. The GTFP framework captures economic output, energy input and selected operational undesirable outputs, but it does not fully capture upstream equipment production, construction-stage emissions, water consumption or end-of-life hardware impacts.

The moderating effect of green computing capacity further qualifies this relationship. The results show that the green productivity effect of AI depends on the carbon intensity, energy efficiency, and network coordination of the computing infrastructure that supports AI applications. When computing facilities are cleaner, more energy-efficient, and better coordinated across computing networks, AI applications can be scaled with lower additional environmental costs, making it easier for cities to transform AI capabilities into green productivity gains. In contrast, when green computing capacity is weak, computing-related energy demand may erode part of the efficiency and environmental benefits generated by AI. This finding implies that green computing capacity should be treated as an enabling infrastructure and a boundary condition for AI-driven green transformation, rather than merely as a background technological condition. The relatively large entropy weight of renewable energy support in the GCC index should be interpreted in this context: it reflects substantial cross-regional variation in clean-energy availability, not a claim that physical computing infrastructure alone determines green computing capacity. Thus, cities with stronger renewable energy support can convert a given level of AI technological development into green productivity gains with lower operational carbon pressure.

5.2. Mechanism Interpretation

The mechanism tests provide evidence consistent with three complementary pathways. The green knowledge recombination pathway reflects AI's capacity to expand the search space of green innovation, identify technological complementarities, and support the recombination of dispersed knowledge modules. The carbon energy flow regulation pathway reflects AI's role in improving the perception, prediction, and optimization of energy use, carbon emissions, and pollution discharge in production systems. The green value-chain coordination pathway suggests that AI may help transform firm-level green improvements into value-chain-level coordination by improving information transparency, facilitating the diffusion of green standards, and strengthening supply-chain responsiveness. Therefore, these results are interpreted as supportive, association-based evidence rather than definitive causal mediation; they should be considered together with the theoretical framework and robustness checks.

These pathways suggest that AI-enabled green productivity should be understood as a system-level transformation rather than as a narrow technological application. A focus only on AI patents, digital equipment, or isolated intelligent applications may overlook how AI changes the organization of green knowledge, the controllability of resource-environmental flows, and the coordination logic of value chains. This interpretation is consistent with the article's theoretical claim that AI differs from generic digitalization not only because it improves information processing, but also because it enables knowledge generation, predictive optimization, and cross-boundary coordination. It also implies that substantial green productivity gains are more likely to emerge when AI deployment is coupled with green innovation platforms, energy management systems, and value-chain governance mechanisms.

5.3. Limitations and Future Research

This study has several limitations. First, AI is measured mainly by patent grants. Although this measure captures technology supply and innovation output, it cannot fully represent the intensity and quality of AI adoption at the firm or application level. Future

research could use firm-level AI adoption, industrial robot deployment, model-use data, or AI text-mining measures to construct more granular indicators. Second, green computing capacity is constructed from observable city-level indicators, but data on data-center power usage effectiveness, renewable electricity procurement, and computing resource scheduling are still limited. More detailed infrastructure data would improve measurement accuracy. Third, the mechanism tests are stepwise and should be interpreted as mechanism-consistent evidence rather than formal causal mediation. Future work could adopt structural mediation models, spatial panel models, or quasi-natural experiments to further identify causal channels. Fourth, the analysis is conducted at the city level and does not distinguish sectoral responses. Sector-specific studies of manufacturing, energy, transport and buildings would help clarify how AI generates heterogeneous green productivity effects. Fifth, the baseline model does not explicitly estimate spatial spillovers among cities, although AI technologies, computing resources and green value-chain linkages may diffuse across city boundaries. Future research could use spatial Durbin models, network-spillover designs or regional computing–network data to examine these intercity effects. Finally, the study improves reproducibility by documenting the variable-construction procedure, but more open datasets and code-sharing arrangements would further strengthen verification by future researchers. In addition, the environmental costs of AI infrastructure are broader than the operational indicators available in this city-level panel. A full assessment would require life-cycle data on data-center construction, chip and server production, cooling systems, water use, electronic waste, and regional electricity dispatch. These omissions mean that the positive GTFP relationship should not be interpreted as evidence that AI infrastructure is environmentally costless.

6. Conclusions

6.1. Main Findings

Using panel data for 287 Chinese prefecture-level and above cities from 2005 to 2023, this study examines the relationship between AI technological development and urban green productivity, together with its transmission channels and boundary conditions. The main findings are as follows. First, AI technological development is positively and robustly associated with urban green productivity, and this conclusion remains robust after alternative variable measurements, sample exclusions, adjusted sample periods, winsorization, lagged-regressor checks, and Bartik IV robustness tests. Second, green computing capacity is associated with a stronger positive AI–green productivity relationship, indicating that low-carbon and efficient computing infrastructure may provide an important condition for AI-enabled green transformation. Third, the mechanism tests provide evidence consistent with three transmission channels: green knowledge recombination, intelligent regulation of carbon energy flows, and green value-chain coordination. Fourth, the heterogeneity tests reveal that the positive AI–green productivity relationship is more pronounced in cities with stronger green computing capacity, stronger industrial foundations and weaker resource–environmental constraints. These findings should be interpreted as robust conditional associations concerning city-level AI technological development and operational green productivity, rather than as deterministic causal claims about AI adoption or as a complete assessment of the full life-cycle environmental footprint of AI infrastructure.

6.2. Policy Implications

The policy implications should be interpreted with caution. The results support a positive association between AI technological development and green productivity under favorable green computing and industrial conditions, but they do not imply that AI deployment is automatically green. Policy design should distinguish among AI innovation,

AI adoption, data-center greening, renewable electricity procurement, and sector-specific implementation in manufacturing, logistics, energy, transport, and buildings. In addition, regional coordination in computing resource allocation and green electricity use should be strengthened. These recommendations are therefore framed as policy-relevant implications of the estimated associations, not as evidence that AI deployment alone will necessarily produce green productivity gains in all cities.

First, green computing infrastructure should be strengthened as a basic condition for AI-enabled green transformation. Cities should accelerate the green upgrading of data centers, intelligent computing centers and computing networks, increase the share of renewable electricity, improve data-center energy efficiency and reduce carbon intensity. Cities with strong computing foundations should prioritize green electricity procurement, computing scheduling and computing–network coordination. Cities with weaker foundations should avoid blind investment in high-energy-consuming data centers and make greater use of regional computing resource sharing and green electricity trading.

Second, AI should be deeply embedded in the whole process of green production. Governments should support AI–green technology innovation platforms that combine AI with low-carbon technologies, improve the identification, matching and transformation of green knowledge, and promote AI applications in energy monitoring, carbon accounting, equipment optimization and pollution-control dispatch. At the same time, leading firms and industrial platforms should be encouraged to apply AI to green procurement, green production, green logistics, green certification and green services, so that green value-chain coordination can move from isolated pilots to chain-level transformation.

Third, differentiated city policies are needed. Cities with high green computing capacity can take the lead in building AI–green application demonstration zones and green intelligent computing platforms. Cities with strong industrial foundations should promote AI-enabled manufacturing upgrading, intelligent manufacturing, and low-carbon supply-chain coordination. Resource-constrained and high-pressure cities should prioritize AI applications in energy saving, pollution control, resource recycling and traditional industrial retrofitting, while preventing technology investments from becoming disconnected from industrial scenarios. Overall, an effective policy system should align computing support, industrial absorption, and green transition objectives.

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Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request. A variable dictionary, data-source description, and indicator construction procedure are provided in the appendices to facilitate reconstruction of the main variables.

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Appendix A. Measurement of Green Productivity

Green productivity is measured by green total factor productivity (GTFP). Compared with conventional total factor productivity, GTFP incorporates energy inputs and environmental constraints into the production framework and accounts for undesirable outputs such as carbon emissions and pollutant discharge. It therefore better reflects the efficiency of economic growth under resource and environmental constraints.

Existing approaches to productivity measurement include the Solow residual method, stochastic frontier analysis (SFA), and traditional data envelopment analysis (DEA). However, these methods may not adequately deal with undesirable outputs and may therefore overestimate the efficiency of decision-making units. The slack-based measure (SBM) model is non-radial and non-oriented, which enables it to account for input redundancy, desirable output shortfalls, and undesirable output excesses. Following the DEA literature, this study adopts an undesirable output Super-SBM model to measure city-level green productivity. In implementation, each city-year observation is regarded as a decision-making unit, and the production frontier is constructed within each year under variable returns to scale. This setting is used because Chinese cities differ substantially in economic scale, industrial structure, and factor endowment, and a year-specific frontier avoids imposing a single pooled technology frontier across the whole 2005–2023 period. This model can further distinguish efficient decision-making units and allows efficiency scores to exceed 1, thereby improving the comparability of cities located on the efficient frontier.

Assume that there are N decision-making units (DMUs). Each DMU uses m inputs to produce s_1 desirable outputs and s_2 undesirable outputs. Let $x \in R_m^+$, $y^g \in R_{s_1}^+$, and $y^b \in R_{s_2}^+$ denote the input vector, desirable output vector, and undesirable output vector, respectively. The production possibility set can be defined as follows:

$$P(x) = \left\{ (x, y^g, y^b) \mid x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \lambda \geq 0 \right\}$$

where X , Y^g , and Y^b represent the input matrix, desirable output matrix, and undesirable output matrix, respectively, and λ is the intensity vector used to construct the production frontier.

For the evaluated DMU o , the undesirable output Super-SBM model is specified as follows:

$$\rho_o^* = \min \frac{\frac{1}{m} \sum_{i=1}^m \frac{\bar{x}_i}{x_{io}}}{\frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{\bar{y}_r^g}{y_{ro}^g} + \sum_{q=1}^{s_2} \frac{\bar{y}_q^b}{y_{ro}^b} \right)}$$

subject to

$$\begin{aligned} \bar{x} &\geq \sum_{j=1, j \neq o}^N \lambda_j x_j, \bar{y}^g \leq \sum_{j=1, j \neq o}^N \lambda_j y_j^g, \bar{y}^b \geq \sum_{j=1, j \neq o}^N \lambda_j y_j^b, \\ \bar{x} &\geq x_o, \bar{y}^g \leq y_o^g, \bar{y}^b \geq y_o^b, \lambda_j \geq 0, j = 1, \dots, N, j \neq o. \end{aligned}$$

In the above model, ρ_o^* denotes the green productivity score of city o . A higher value indicates stronger green productivity. The variables $\bar{x}$, $\bar{y}^g$, and $\bar{y}^b$ denote the adjusted input, desirable output, and undesirable output of the evaluated DMU, respectively.

The input indicators include capital, labor, and energy. Capital input is measured by city-level capital stock estimated using the perpetual inventory method with 2005 as the base year. Labor input is measured by the number of urban employees. Energy input is measured by total primary energy consumption and converted into standard coal equivalents. The desirable output is real GDP, deflated to constant 2005 prices. The undesirable outputs include industrial CO₂ emissions, industrial wastewater discharge, and industrial smoke and dust

emissions. To ensure the applicability of the DEA framework, undesirable output indicators are processed using a linear data transformation method where necessary. For environmental and energy variables, observations with abnormal jumps or missing values were checked against adjacent years and official yearbooks; interpolation was used only when the missing segment was short, and the surrounding observations were internally consistent.

Appendix B. Variable Dictionary and Indicator Construction Procedure

This appendix summarizes the main variables and reconstruction procedures used in the empirical analysis. All monetary variables are deflated to constant 2005 prices. Patent variables are aggregated to the prefecture-level city-year level after harmonizing applicant addresses and administrative boundary changes.

Table A1. Definitions, measurements and data sources of the main variables.

Variable		Meaning	Construction and Source
GTFP	Urban green productivity		Undesirable output Super-SBM model using capital, labor, and energy inputs, real GDP as desirable outputs, and industrial CO ₂ , wastewater, smoke and dust as undesirable outputs; official statistical yearbooks.
AI	AI technological development		Granted AI patents identified using the CNIPA Key Digital Technology Patent Classification System (2023), matched to cities by applicant address and measured in units of 10,000 patents.
GCC	Green computing capacity		Entropy-weighted composite index covering computing infrastructure capacity, green energy support, low-carbon operating efficiency and computing–network coordination.
GKR	Green knowledge recombination		Number of granted AI–green integrated patents identified from the intersection of AI patent classes and green patent taxonomies, aggregated at the city-year level.
CEFR	Carbon energy flow regulation		Entropy-weighted index based on energy intensity, electricity intensity, carbon intensity, carbon productivity, and electricity output efficiency.
GVCC	Green value-chain coordination		Coordinated agglomeration between manufacturing and producer services, used as a proxy for green value-chain coordination.

Table A2 reports the detailed indicator list, data sources and entropy weights used to construct the green computing capacity index.

Table A2. Indicator system, data sources and entropy weights of the green computing capacity index.

Dimension	Indicator and Measurement	Sign	Entropy Weight
Computing infrastructure capacity	Internet broadband infrastructure, measured by broadband users per 100 persons	+	0.1363
	Mobile network infrastructure, measured by mobile phone users per 100 persons or mobile communication base stations where available	+	0.1835
Green energy support	Renewable energy supply, measured by renewable electricity generation or installed renewable energy capacity at the provincial level	+	0.5597
	Electricity carbon intensity, measured by CO ₂ emissions per unit of electricity consumption at the provincial level	−	0.0051

Table A2. Cont.

Dimension	Indicator and Measurement	Sign	Entropy Weight
Low-carbon operating efficiency	Energy intensity, measured by total energy consumption per unit of real GDP	—	0.0102
	Carbon intensity, measured by industrial CO ₂ emissions per unit of real GDP	—	0.0020
Computing–network coordination and utilization	Network connectivity, measured by internet penetration rate or mobile internet users per 100 persons	+	0.0514
	Information transmission capacity, measured by telecom business volume or internet bandwidth where available	+	0.0519

Notes: ‘+’ denotes a positive indicator and ‘—’ denotes a negative indicator.

All indicators are standardized before aggregation. For a positive indicator, $x' = (x - \min)/(\max - \min)$; for a negative indicator, $x' = (\max - x)/(\max - \min)$. The entropy weight of indicator j is $w_j = d_j/\sum d_j$, where $d_j = 1 - e_j$ and e_j is the entropy value calculated from the standardized city-year panel. The main data sources include the *China City Statistical Yearbook*, *China Statistical Yearbook*, *China Energy Statistical Yearbook*, provincial energy statistical yearbooks, provincial energy balance sheets, MIIT communications statistics, and standard emission coefficients. Specifically, communication-related indicators are mainly obtained from city-level statistical yearbooks and MIIT communications statistics; renewable energy supply and electricity carbon intensity are constructed at the provincial level and matched to prefecture-level cities by province; energy intensity and carbon intensity are calculated using the same energy consumption and CO₂-emission data sources as those used in the GTFP measurement. Short missing segments are interpolated only when adjacent observations are internally consistent. Entropy weights are rounded to four decimal places; therefore, their sum may differ slightly from one due to rounding. The renewable energy support indicator receives the largest entropy weight because it displays relatively large information variation in the standardized city-year panel. Since this indicator is measured at the provincial level and matched to cities by province, the GCC index should be understood as combining city-level computing/network conditions with broader regional renewable energy support. This treatment does not invalidate the index, but it means that the empirical interpretation should emphasize operational green computing conditions rather than only city-level computing facility scale.

Appendix C. Additional Robustness, Heterogeneity, Diagnostic Procedures

Table A3. Descriptive statistics.

Variable	N	Mean	SD	Min	Max	p50
GTFP	5453	0.315	0.143	0	1.193	0.292
AI	5453	0.091	0.503	0	11.37	0.004
GCC	5453	0.095	0.100	0	1	0.06
fdi	5453	0.102	0.317	0	4.773	0.015
edu	5453	0.932	1.671	0.002	14.89	0.363
GDP	5453	0.425	0.371	0	2.821	0.362
urb	5453	0.512	0.189	0	1	0.509
net	5453	1.887	1.956	0	18.99	1.307
sci	5453	0.022	0.024	0	0.229	0.015

Table A4. Correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GTFP	1.000								
AI	0.308 ***	1.000							
GCC	0.296 ***	0.113 ***	1.000						
fdi	0.185 ***	0.323 ***	0.008	1.000					
edu	0.236 ***	0.412 ***	0.246 ***	0.320 ***	1.000				
GDP	0.449 ***	0.374 ***	0.442 ***	0.300 ***	0.364 ***	1.000			
urb	0.289 ***	0.274 ***	0.344 ***	0.307 ***	0.376 ***	0.571 ***	1.000		
net	0.367 ***	0.388 ***	0.466 ***	0.324 ***	0.327 ***	0.634 ***	0.566 ***	1.000	
sci	0.209 ***	0.402 ***	0.317 ***	0.312 ***	0.285 ***	0.423 ***	0.389 ***	0.457 ***	1.000

Note: *** indicate significance at the 1% level.

Table A5. Multicollinearity test.

Variable	VIF	1/VIF
net	2.16	0.463
GDP	2.05	0.487
urb	1.75	0.570
GCC	1.48	0.677
sci	1.47	0.678
AI	1.47	0.679
edu	1.40	0.716
fdi	1.32	0.759
Mean VIF	1.64	—

Note: VIF denotes the variance inflation factor, and 1/VIF denotes tolerance. All VIF values are well below the conventional threshold of 10, indicating that multicollinearity is not a serious concern.

Table A6. Robustness checks using alternative GCC constructions.

Variable	(1) Equal-Weighted GCC	(2) PCA-Based GCC
AI	0.018 *** (0.002)	0.026 *** (0.002)
GCC	0.002 (0.002)	0.004 ** (0.002)
AI * GCC	0.011 *** (0.002)	0.008 *** (0.001)
fdi	−0.078 *** (0.014)	−0.080 *** (0.014)
edu	0.024 *** (0.003)	0.023 *** (0.003)
GDP	0.079 *** (0.008)	0.078 *** (0.008)
urb	−0.062 *** (0.011)	−0.062 *** (0.011)
net	−0.002 (0.001)	−0.002 (0.001)
sci	−0.377 *** (0.080)	−0.378 *** (0.080)
_cons	0.309 *** (0.007)	0.311 *** (0.007)
City	Yes	Yes
Time	Yes	Yes
N	5453	5453
R ²	0.733	0.733

Notes: Robust standard errors clustered at the city level are reported in parentheses. **, and *** indicate significance at the 5%, and 1% levels, respectively. GCC denotes green computing capacity.

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