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The Impact of Government Green Procurement on Corporate Carbon Emission Reduction: A Dual Mediation Perspective of Artificial Intelligence and Green Finance

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Abstract

This study uses data of A-share listed companies in Shanghai and Shenzhen from 2020 to 2024. We manually collect green procurement lists from official government procurement websites and match them with firm samples. Employing the two-way fixed effects model and the Bootstrap method, this paper empirically examines the impact of green public procurement on corporate carbon reduction. The results show that green public procurement significantly improves firms' carbon reduction performance. Mechanism analysis indicates that AI adoption and government green subsidies further strengthen this effect. Heterogeneity tests reveal that the impact is more pronounced for state-owned enterprises, high-tech firms and enterprises in regions with advanced digital economies. Accordingly, we propose suggestions including strengthening the driving role of green procurement, promoting coordination between green procurement and digital technology, optimising the allocation of green funds, and implementing targeted differentiated incentives. This research helps clarify the internal mechanism of green public procurement on carbon emission reduction performance and provides references for improving relevant practices in carbon emission reduction.

Keywords: government green procurement; carbon emission reduction; artificial intelligence; green fiscal funds; sustainable development

1. Introduction

1.1. Research Background and Problem Statement

Against the backdrop of intensifying global climate change, carbon reduction has evolved from a domain of environmental governance practice into a globally shared imperative and constitutes one of the core theoretical agendas of sustainable development research worldwide [1–3]. As the largest developing economy and a leading carbon emitter, China has consistently demonstrated a responsible commitment by pledging carbon peaking and carbon neutrality goals at successive international forums, including the United Nations Climate Change Conferences, and by embedding climate action into its national development blueprint. Firms constitute the principal agents for delivering carbon reduction targets. However, under modern networked and collaborative production paradigms, corporate emissions are widely dispersed across the numerous nodes of supply-chain networks. Consequently, autonomous low-carbon transitions undertaken by individual firms are inadequate for overcoming systemic mitigation barriers, a reality that challenges

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the conventional theoretical premise that firms can autonomously enhance environmental performance through their own governance efforts [4,5].

Government green procurement, as a critical fiscal instrument for guiding and regulating corporate behaviour, plays an indispensable role in implementing the dual carbon strategy and has emerged as a pivotal policy lever for steering corporate environmental conduct and nurturing green industries across multiple jurisdictions [6,7]. Existing studies show that green public procurement sends environmental signals to the market and reshapes corporate incentives, thereby boosting the development of low-carbon industries. Against China's institutional backdrop, top-level policies, including the comprehensive green transition strategy and carbon footprint management, have shifted the focus of green procurement from selecting eco-friendly products to regulating corporate carbon emissions. This has spurred academic research on the mechanisms and application boundaries of green public procurement in driving corporate carbon reduction during economic transition.

Nevertheless, the existing literature has predominantly concentrated on green technological innovation as a single transmission channel, with limited systematic investigation of the two equally consequential pathways of digital empowerment and fiscal leverage. This gap remains somewhat misaligned with the prevailing trend of deep integration between the digital and green economies and the precision deployment of fiscal resources to support the green transition. Currently, large-scale AI models, as a core breakthrough in new-generation information technology, have demonstrated enormous application potential in low-carbon scenarios such as intelligent production scheduling, smart energy management, and product carbon footprint tracking. They have emerged as vital technological support for overcoming the inadequate precision and low efficiency of corporate carbon reduction efforts [8,9]. Meanwhile, insufficient green funding remains a core bottleneck constraining enterprises from undertaking low-carbon technological upgrading and green production transformation. Government green funding, as dedicated guiding capital, can effectively alleviate corporate financial constraints and leverage social capital participation, providing essential financial support for corporate carbon reduction [10]. Therefore, the central research questions of this study are as follows: Does GGP promote corporate carbon emission reduction through facilitating AI technology adoption and leveraging dedicated green funding? What is the relative importance of these two transmission pathways, and do they exhibit synergistic effects?

1.2. Research Content and Contributions

Centred on the aforementioned research questions, this study addresses the following aspects. (1) Based on micro-level firm panel data, this study empirically examines the direct impact of GGP on corporate carbon reduction performance to establish the baseline policy effect [11,12]. (2) A mediation analysis framework is constructed to reveal the mediating transmission mechanisms of AI penetration rates and government green funding in the relationship between GGP and corporate carbon emission reduction. (3) Through path coefficient comparison and interaction term analysis, the relative importance and synergistic relationship of the two mediating pathways are clarified [13,14]. (4) Heterogeneous effects are analysed across dimensions of firm ownership structure, industry technological attributes, and regional digital economy development levels [15,16].

The contributions of this study are reflected in three principal aspects. First, it transcends the limitations of existing research that focuses on a single technological innovation pathway by constructing an innovative theoretical framework spanning demand incentives, digital empowerment, financial provision, and emission reduction performance [6]. This enriches the research on GGP policy transmission mechanisms and extends the boundaries of research on green procurement and environmental governance theory. Second,

it integrates AI and funding indicators within a unified mediation mechanism analysis, achieving an organic integration of macro-level technological trends and micro-level firm behaviour, thereby enhancing the systematicity and precision of the mechanism analysis. Third, by employing micro-level firm panel data from 2020 to 2024, this study precisely captures the latest practices of GGP policies and the rapid penetration of AI technology during the 14th Five-Year Plan period, ensuring the timeliness and practical relevance of the research conclusions and addressing the data lag in existing studies.

1.3. Research Significance

From a theoretical perspective, this study systematically investigates the dual-pathway mechanism by which GGP drives corporate carbon emission reduction, addressing the deficiency in existing research on digital empowerment and financial leverage pathways. It enriches the theoretical content of green procurement and environmental governance and offers a new perspective on the mechanisms of demand-side policy instruments. Additionally, the analytical framework of demand incentives, dual-pathway empowerment, and emission-reduction performance offers a referenceable paradigm for subsequent research, promoting the systematisation and refinement of related studies.

From a practical standpoint, this study provides decision-making references for governments to optimise the design of green procurement policies. By identifying the key links through which GGP drives corporate carbon reduction via digital empowerment and financial leverage, it offers practical guidance for policymakers to refine the specific pathways of incorporating carbon footprint into government procurement, optimise green funding allocation methods, and promote the synergistic implementation of AI technology and green procurement policies. It also provides practical guidelines for enterprises to seize the opportunities presented by GGP and accelerate their green transformation.

2. Literature Review and Commentary

2.1. Economic and Environmental Effects of Government Green Procurement

Driven by global environmental governance and sustainable development goals, green public procurement has become a key demand-side policy tool for advancing the green transition. Numerous studies have verified that it can motivate corporate green innovation and ease financing constraints through signal transmission, demand guarantee, and reputation restraint. Empirical studies on China provide further context-specific evidence. Li documents a positive association between the scale of government procurement and green innovation and identifies enhanced climate awareness as a key facilitator of green technological progress [17]. Zou et al. adopting a staggered difference-in-differences approach, confirm that GGP, by easing financing constraints and elevating environmental salience, significantly raises both the volume and quality of corporate green innovation and underscore its catalytic role in knowledge diffusion along industrial chains [18]. Lei and He, utilising a quasi-natural experiment, find that firms admitted onto the green procurement catalogue exhibit markedly improved environmental performance, with executive green cognition and green investment incentives identified as the operative channels; this effect is more pronounced among state-owned and large enterprises [19].

Since 2020, GGP in China has entered a new phase of policy upgrading and the reconstruction of demand standards. The Ministry of Finance and associated authorities have accelerated the development of green procurement demand-standard systems, progressively incorporating carbon footprint requirements into public procurement and reorienting policy logic from green product preferences toward carbon reduction outcomes. The Three-Year Action Plan for Government Procurement covering 2024 to 2026, which targets the rectification of market order, the construction of legal frameworks, and the

promotion of industrial development, further expands the mandatory procurement scope of green building materials and reinforces low-carbon orientation and digital regulatory supervision, thereby furnishing a novel institutional setting for academic research in this domain. Overall, while the existing literature largely confirms the beneficial role of GGP, it remains confined to the singular pathway running from GGP through green technological innovation to performance, without integrating digital empowerment and fiscal leverage into a unified framework. This represents disjunction from the policy frontier.

2.2. Influencing Factors and Driving Pathways of Corporate Carbon Emission Reduction

In contemporary discourse, carbon reduction has evolved beyond a purely environmental concern into a complex system intricately bound up with economic structure, technological innovation, and social behaviour. Achieving the dual carbon goals, therefore, requires not only top-level policy design but also multi-stakeholder coordination and the convergence of multiple mechanisms. Early studies typically focused on a single policy instrument. For example, Chelly et al., by comparing three jurisdictions employing distinct progressive carbon tax strategies, demonstrate that initial green investment decisions hinge on the targeted level of carbon tax rather than its formal structure, with implications for selecting tax forms aligned with the performance of available green technologies [20]. Li et al. [21] find that peer incentive funds among firms encourage active mitigation strategies and induce more proactive government regulation. A broader stakeholder perspective reveals further complexity in mitigation practice [21]. Wang et al. from a stakeholder lens, identify manufacturing enterprises as exerting the greatest influence on emission reduction intensity, whereas financial institutions exert the weakest [22].

From a supply-chain perspective, Jiang et al. demonstrate that emission reduction effects are not transmitted linearly but are conditioned by the intensity of technological spillovers [23]. Wang et al. find that rising consumer low-carbon preferences not only motivate manufacturers to enhance mitigation investment but also indicate that retailer-led joint emission reduction outperforms manufacturer-only mitigation [24]. Chen and Wang find that region-level carbon mitigation generates substantial green spillover effects, helping firms access green credit, attract media attention, and engage green investors, thereby improving corporate ESG performance [25].

While research perspectives in this domain continue to broaden, a substantial portion of the literature remains fragmented. Policy, technology, finance, and supply-chain dimensions are typically examined in isolation, with limited effort to integrate GGP, digital technology, and green fiscal funds into a coherent analytical framework. There is a particular lack of research on how policies combine technology and capital effects.

2.3. Applications of Artificial Intelligence in Green Transformation

The current wave of technological revolution, represented by generative artificial intelligence, is profoundly reshaping the production methods, organisational forms, and innovation paradigms of enterprises. AI is no longer merely an efficiency-enhancing tool but has begun to deeply embed itself as a general-purpose technology and cognitive enhancer throughout the entire process of corporate green transformation. From the perspective of functional positioning and application logic, generative artificial intelligence differs substantially from conventional artificial intelligence applied in carbon management scenarios. Conventional artificial intelligence is mainly used for standardised tasks such as data monitoring, indicator calculation and process control to execute preset analytical instructions. Generative artificial intelligence is equipped with capabilities including content generation, logical reasoning, autonomous decision making and human–computer interaction. It can be deeply involved in high-level work covering scheme design, information interpretation

and research on complex issues, which greatly expands its application scope and improves the overall intelligence level. Early research primarily focused on how AI affects environmental performance through direct pathways such as optimising production processes and reducing energy consumption, while recent studies have shifted toward cognitive mechanisms, governance synergy, and systemic restructuring. For instance, Si et al. constructed a generative AI-based green product recommendation system that significantly enhanced users' cognitive fluency by translating complex carbon footprint information into personalised content adapted to consumers' cognitive styles, thereby nearly doubling the purchase conversion rate for low-carbon products [26]. Feng et al. demonstrated a significant positive correlation between AI adoption and green innovation efficiency, confirming the potential of AI as a catalyst for sustainable development and emphasising the importance of organisational capabilities in realising these benefits [27].

Related studies have shown that AI's impact on corporate green transformation is multidimensional and multi-pathway. For example, Li found that AI development significantly enhances corporate green total factor productivity and further demonstrated that AI contributes to improved green technology efficiency and green technological progress [28]. Similarly, Jiang et al. also confirmed that AI drives corporate green transformation by strengthening enterprises' emphasis on R&D and their green innovation capabilities [29]. Mansour et al. found that AI capabilities promote green innovation efficiency in firms from emerging economies, and this effect significantly depends on the firm's own ESG foundation, exhibiting certain contextual characteristics [30]. Frontier applications further demonstrate that AI can deliver full-chain carbon data tracking, dynamic optimisation of emission factors, and precise identification of carbon leakage, thereby underpinning precision-oriented decarbonization.

For example, the Chinese Academy of Sciences' Panshi Yuheng large carbon accounting model enables panoramic carbon traceability and dynamic accounting, while the Chat–LCA system, which integrates large language models with life cycle assessment, substantially enhances the intelligence and efficiency of carbon footprint calculation. Recent breakthroughs in AI applied to carbon management exemplify the rapid maturation of this field. Although extant studies provide a theoretical basis for AI-enabled mitigation, they commonly treat AI as a self-determined corporate choice or an exogenous shock, overlooking the incentive effect of GGP, as a demand-side signal, on AI adoption. Consequently, the logical chain running from policy through technology to mitigation has remained underexplored.

2.4. Guiding and Incentive Effects of Government Green Funding

Unlike green public procurement, which acts as a market-oriented instrument on the demand side and drives corporate green production through government preference for green products and corresponding transaction payments, green subsidies serve as supply-side fiscal incentives. They offset firms' costs in green investment via non-repayable fiscal funds or tax reductions without linking to procurement activities. The two policy tools differ fundamentally in attributes, capital flows and operational mechanisms. Green funding is a core policy tool for correcting environmental externalities, alleviating corporate financing constraints, and driving low-carbon transformation [31,32]. As the global sustainability agenda advances, the 2025 Standards for Evaluation of Green and Low-Carbon Products have set new requirements for corporate carbon management and green supply chains, making green funds an increasingly important guiding force. The green supply-chain initiative for China's real estate sector, jointly launched by HSBC China and the Beijing Society for Entrepreneurs and Environmental Protection, has proven that combining green

procurement with financial support can generate synergies and drive emission reduction and quality improvement across supply chains.

Several mainstream economic theories provide solid theoretical support for government intervention in green investment. Endres et al. extend the classical framework of dual market failures and analyse the effectiveness of jointly using environmental liability law and R&D subsidies to internalise dual externalities [33]. Stavins et al. also note that beyond the externalities generated by pollution itself, the innovation and diffusion processes entail additional externalities and other market failures that further undermine corporate incentives to invest in environmental technologies [34]. Meanwhile, financing constraint theory indicates that green investment inherently involves large upfront capital requirements, long payback periods, and high risk levels, while the traditional financial system struggles to meet the long-term capital needs of green innovation [31,35]. Therefore, fiscal subsidies, green credit, green procurement, and other forms of government funding are regarded as compensatory mechanisms to address market failures and leverage private capital. Guo et al. also confirmed that government environmental investment can directly enhance green development levels [36]. Liew et al. further confirmed that the synergy between government capital expenditure and carbon policy effectively guides the green investment preferences of institutional investors, suggesting that government funding represents not merely resource injection but also a form of endorsement and guidance [37].

While existing literature has examined the digital and the fiscal pathway separately it has not articulated their interactive mechanism within a unified framework. Specifically, how GGP stimulates AI adoption and mobilises green fiscal funds, and whether synergistic interactions emerge between these two pathways, have not been adequately addressed.

2.5. Literature Summary

Existing studies on green public procurement, carbon emission reduction, AI empowerment and green funds have laid a solid theoretical foundation for this research. However, several limitations remain. First, most studies rarely integrate digital empowerment and green funds into a unified model, failing to fully explain policy transmission mechanisms. Second, prior research overlooks the incentive effect of green public procurement on corporate digital transformation, and the synergies between the two have not been empirically verified. Third, most samples in previous studies end around 2020, which cannot reflect subsequent reforms of green procurement policies and the application of AI in carbon management, resulting in limited timeliness of their conclusions.

Based on the three major limitations of existing studies, this paper puts forward three theoretical contributions. First, it establishes an integrated dual-mediation framework covering artificial intelligence and green funds to break the constraint of single-path analysis. By synthesising relevant research, this paper clarifies the independent effects and relative importance of the two paths and improves the framework of policy transmission mechanisms. Second, it identifies the guiding effect of GPP on AI adoption and empirically tests the synergies between digital empowerment and green funds. This fills the research gap regarding path interaction and realises multi-dimensional mechanism integration. Third, this study uses panel data on A-share-listed companies in Shanghai and Shenzhen from 2020 to 2024. Combining the post-2020 reforms of green procurement policies and cutting-edge practices of generative AI in carbon management, it enhances the timeliness and practical relevance of the research.

In sum, this study does not negate prior single-dimension investigations but builds upon them through integration, extension, and rigorous testing. By combining multiple theoretical perspectives with frontier empirical evidence, we offer a more systematic and

forward-looking theoretical account and empirical foundation for understanding how GGP drives corporate carbon reduction in the digital era.

3. Theoretical Analysis and Research Hypotheses

Building upon the literature review, this chapter integrates institutional theory, signalling theory, and resource dependence theory to construct a theoretical analytical framework spanning demand incentives, dual-pathway empowerment, and emission reduction performance. It systematically elaborates on the internal logic through which GGP influences corporate carbon emission reduction and proposes the research hypotheses.

3.1. Theoretical Foundations

Institutional theory provides the foundational constraint and legitimacy logic for the GGP-driven decarbonisation framework and underpins the entire theoretical architecture. The theory posits that organisational behaviour and structure are shaped by the institutional environment, including regulatory, normative, and cultural cognitive pressures [38,39]. From an institutional perspective, the government, as the principal architect of the institutional environment, conducts green procurement as a demand-side institutional arrangement that exerts coercive isomorphism (for instance, embedding green procurement requirements into compliance assessments), mimetic isomorphism (encouraging firms to follow industry benchmarks in responding to green procurement requirements), and normative isomorphism (cultivating industry consensus on green business practices). These three pressures impose rigid constraints alongside soft guidance on firms. Such institutional pressures induce firms to recalibrate their production and operational practices and to embed carbon reduction into corporate strategy. To secure procurement contracts, satisfy compliance, and maintain social legitimacy, firms are motivated to expand green investment and innovation, which constitutes the precondition for GGP to take effect [40,41]. This logic directly supports the main effect Hypothesis H1 and explains how green public procurement positively promotes corporate carbon emission reduction. Institutional theory also clarifies that legitimacy enhancement is a central objective of corporate carbon reduction and elucidates how GGP drives green procurement and green product and process innovation within firms. These innovative activities reflect both organisational responses to institutional pressures and direct pathways for improving carbon reduction performance [42]. In addition, institutional theory can explain the heterogeneous policy effects caused by corporate ownership. State-owned enterprises maintain closer institutional ties with governments and respond more actively to regulatory and normative pressures, which provides the core theoretical foundation for the heterogeneity Hypothesis H4a.

Signal theory complements institutional logic by revealing the information transmission and guidance mechanisms through which green public procurement drives corporate low-carbon transition. It also serves as a critical link between institutional pressures and corporate practical actions. In markets characterised by information asymmetry, parties holding superior information can convey private information through observable actions [43–45]. The government, as the most extensive and most creditworthy purchaser in the market, transmits an authoritative and credible signal through its green procurement behaviour. Such behaviour not only embodies institutional pressure but also conveys core information regarding the orientation of future green technology, the focal points of policy support, and the stability of demand for green products [46]. This signal transmission alleviates information asymmetry between external investors and enterprises, guides capital and social resources toward low-carbon sectors, and provides indirect resource support for corporate low-carbon development. Meanwhile, such signals steer corporate managers to prioritise relevant strategies and prompt firms to allocate more resources to carbon emis-

sion reduction, particularly by adopting digital technologies to achieve efficient emission cuts [47]. This transmission mechanism supports the mediation Hypotheses H2a and H2b and lays a logical foundation for the synergy effect Hypothesis H3. While institutional theory emphasises restrictive effects, signal theory places greater emphasis on directional guidance. It also explains why enterprises actively adopt efficient and sustainable emission reduction strategies rather than merely responding passively to institutional pressures.

Resource dependence theory provides the core resource support for GGP-driven carbon mitigation and serves as the enabling condition for the operation of the two theories above, forming a layered logic of constraint, guidance, and support alongside institutional and signalling theories. Resource dependence theory holds that organisational survival and development depend on the acquisition of critical resources from the external environment [48,49]. Green public procurement provides enterprises with two key resources. The first is stable market orders generated by green procurement contracts, and the second is supporting fiscal subsidies for green development [17,46]. These resources can not only ease financing constraints and pressures on technological investment during corporate green transition, but also follow the resource allocation orientation of signal theory. The capital flow signals released by green public procurement can only be translated into practical emission reduction actions with the support of matched resource supply. The complementary relationship between these resources verifies Hypothesis H3 and further consolidates the theoretical basis for H2a and H2b. Resource dependence theory also reinforces the constraint effect of institutional theory, since firms seeking sustained access to the critical resources delivered by GGP proactively adjust their strategies to align with government green requirements and invest in domains capable of enhancing carbon reduction performance, such as adopting AI to optimise energy consumption and emissions [1]. Differences in firms' resource transformation capabilities and regional resource endowments lead to divergent policy outcomes, which explains the industry heterogeneity Hypothesis H4b and regional heterogeneity Hypothesis H4c.

Based on the above theories, this study constructs the following theoretical framework. GGP, as a demand-side institutional incentive and market signal, not only induces emission reduction through direct compliance pressure but also empowers enterprises through two critical pathways. The first is the digital empowerment pathway, wherein procurement demand signals incentivise firms to increase the adoption of digital technologies such as AI, improving emission reduction efficiency through intelligent means. The second is the financial provision pathway, in which green funding accompanying procurement activities directly provide resource support for corporate emission reduction activities. These two pathways work in concert to ultimately drive improvements in corporate carbon emission reduction performance.

3.2. Research Hypotheses

H1. *Government green procurement has a significant promoting effect on corporate carbon emission reduction performance.*

According to institutional theory, GGP imposes compliance and normative pressures on firms by setting explicit environmental standards and procurement thresholds [43,50]. Simultaneously, per signalling theory, obtaining a green procurement contract signifies government certification. From the resource dependence perspective, this not only brings stable market resources but also transmits a positive signal to external stakeholders that the firm possesses green competitiveness, motivating firms to continually improve their environmental performance to safeguard their reputation and market position [47]. There-

fore, this study expects that the greater the degree of GGP support received by a firm, the better its carbon emission reduction performance.

H2a. *The penetration rate of AI mediates the relationship between GGP and corporate carbon emission reduction.*

GGP imposes stringent requirements on product carbon footprints and environmental performance, thereby compelling firms to optimise production processes and adopt refined management practices. As a large-scale, high-credibility market resource, GGP tenders attract intense competitive participation, and the GGP scoring system places substantially greater weight on green performance and carbon reduction efficiency, thereby transforming these dimensions into core determinants of bidding success. AI confers distinctive advantages in process optimisation and intelligent production scheduling, enabling firms to achieve both energy efficiency and process-level emission reduction. On one hand, real-time analytics of equipment operating data refine process parameters and reduce energy waste and emissions during production [51]. On the other hand, intelligent scheduling synchronises raw material supply, production stages, and product transportation, lowering carbon intensity across the entire value chain. Empirical evidence indicates that under the competitive landscape generated by GGP, firms proactively integrate AI to enhance green competitiveness and improve bidding success, and the diffusion of AI further amplifies these advantages through smarter and more efficient mitigation. Accordingly, GGP enhances corporate carbon reduction performance by promoting the adoption and diffusion of AI [52,53].

H2b. *Government green funding subsidies mediate the relationship between GGP and corporate carbon emission reduction.*

Relevant policy documents require improvements to the GGP framework and strengthened financial support via subsidies and priority funding, mainly for enterprises that meet GGP standards or hold relevant qualifications and contracts. In sectors such as green building materials and new energy vehicles, companies with GGP contracts are eligible for green subsidies and receive priority funding for low-carbon renovation and clean equipment procurement, forming a transmission path from GGP to green subsidies. From the perspective of signal transmission, GGP contracts serve as official government endorsement. They mitigate information asymmetry between the government and enterprises, help certify firms' green credentials and raise their chances of obtaining subsidies. This signalling effect further strengthens the link between GGP and green fiscal subsidies. In summary, through policy coordination and official signalling, GGP increases enterprises' access to green fiscal subsidies, eases financing constraints for low-carbon technology upgrading and emission reduction R&D, and ultimately motivates corporate carbon reduction efforts and improves emission reduction performance.

H3. *The penetration rate of AI and government green funding subsidies exhibits synergistic reinforcement effects in the process through which GGP affects corporate carbon emission reduction.*

According to complementary assets theory, different types of complementary assets used in combination generate synergistic value that exceeds the sum of their independent contributions, with the core logic being that the two asset classes mutually reinforce one another and offset individual limitations. In this study, the penetration rate of artificial intelligence represents technology-based complementary assets that serve as digital carriers for low-carbon production and intelligent management. Government green financial

subsidies serve as complementary financial assets that provide resource guarantees for technology implementation and project operations. As two core pathways through which green public procurement drives corporate carbon emission reduction, the two factors are not independent of each other. Instead, they form a mutually reinforcing synergistic relationship based on complementarity. Green fiscal subsidies provide essential support for AI adoption and lower the cost of technology uptake. AI deployment, computing service procurement, and the customisation of decarbonisation solutions all require substantial upfront investment, and green fiscal subsidies may be earmarked for these expenditures, thereby alleviating financial pressure, lowering adoption thresholds and risks, and enabling rapid implementation of AI large models that support their mitigation function. Reciprocally, AI permeation enhances the efficiency of green subsidies and amplifies their mitigation impact. AI tools can accurately calculate carbon footprints, optimise the allocation of low-carbon investments, and monitor mitigation outcomes in real time [54,55], identifying the optimal target domains for green fiscal resources, avoiding wastage, and ensuring that each subsidy is directed toward the highest-impact mitigation activities.

In sum, the two factors form bidirectional synergy on the basis of complementary asset attributes. Green fiscal subsidies reduce the cost of AI adoption and accelerate technology diffusion, while AI permeation enhances subsidy efficiency and magnifies fiscal effectiveness, jointly reinforcing the driving role of GGP in corporate carbon reduction.

H4a. *Compared with non-state-owned enterprises, the promoting effect of GGP on carbon emission reduction is more significant for state-owned enterprises.*

State-owned enterprises maintain closer connections with the government, are more sensitive to policy signals, and have stronger motivations to fulfil policy-related obligations. Consequently, they may respond more swiftly and thoroughly to GGP by leveraging their associated resources such as funding and technology, to implement emission reductions.

H4b. *Compared with firms in traditional industries, the promotional effect of GGP on carbon emissions reduction is more significant for firms in high-technology industries.*

High-technology industry firms inherently possess stronger technological innovation and absorptive capacities, enabling them to translate green procurement demands into digital technology solutions more rapidly. Their technological foundation makes the effects of the digital empowerment pathway more pronounced.

H4c. *In regions with higher levels of digital economy development, the promoting effect of GGP on corporate carbon emission reduction is more significant.*

Higher levels of digital economy development imply more comprehensive local digital infrastructure, more active data factor markets, and richer talent reserves. These conditions provide a superior external environment for firms to apply digital technologies such as large-scale AI models through the digital empowerment pathway, enabling the policy signals from GGP to be more effectively converted into actual emission reduction outcomes through the technology pathway.

4. Research Design

4.1. Sample Selection and Data Sources

This study uses Chinese A-share listed companies on the Shanghai and Shenzhen Stock Exchanges from 2020 to 2024 as the initial research sample. The sample was processed as follows. (1) Financial and insurance sector listed companies were excluded.

(2) Companies under special treatment, including ST and *ST designations, were excluded. (3) Observations with missing data on key variables were removed. (4) To mitigate the influence of extreme values, all continuous variables were winsorized at the 1st and 99th percentiles. The final dataset is an unbalanced panel.

Data sources: Corporate financial and governance data were obtained from the CSMAR database. Corporate carbon emission data were referenced from the China Emission Accounts and Datasets (CEADSs) and disclosure information from corporate social responsibility reports and environmental reports, with calculations cross-validated using the Guidelines for Accounting Methods and Reporting of Corporate Greenhouse Gas Emissions. GGP data were manually collected and compiled from bid-winning announcements on the China Government Procurement website and its regional subsites. Text recognition technology was employed to screen for procurement contracts explicitly containing keywords such as energy saving, environmental protection, green, low-carbon, and ecological, which were then matched to bid-winning enterprises. Detailed government subsidy data were obtained from the CSMAR database, from which projects related to environmental protection, energy conservation, clean energy, and low-carbon initiatives were filtered and aggregated to derive the green funding subsidy amount. AI-related data were constructed through Python 3.10 web scraping and analysis techniques, performing word frequency analysis on annual reports and board reports of listed companies. Regional data on digital economy development levels were sourced from authoritative index reports, such as the China Digital Economy Development Report published by the Cyberspace Administration of China.

4.2. Variable Definitions

4.2.1. Dependent Variable

Carbon emission reduction performance (CRP) is measured by carbon productivity, defined as the ratio of a firm's total operating revenue to its total carbon emissions (in 10,000 CNY per ton of CO_2). A higher value indicates that the firm generates greater economic output per unit of carbon emissions, reflecting better carbon emission reduction performance. This indicator integrates the dual objectives of economic growth and emission reduction and is a commonly used metric for assessing low-carbon development efficiency.

4.2.2. Independent Variable

Government green procurement (GGP) is measured in two ways: (1) The dummy variable approach (GGP_Dum) assigns a value of 1 if the firm obtained at least one government green procurement contract in a given year and 0 otherwise. (2) The continuous variable approach (GGP_Ratio) measures the ratio of the total value of government green procurement contracts obtained by the firm in a given year to its total operating revenue. The continuous variable is employed to further examine the impact of the procurement scale.

4.2.3. Mediating Variables

(1) AI penetration rate (AI_Penetration) is measured using text analysis, following relevant prior research. This variable is constructed by extracting the total word frequency of terms related to artificial intelligence, large models, machine learning, deep learning, natural language processing, and intelligent algorithms from sections such as the Management Discussion and Analysis and the Business Overview in annual reports of listed companies, divided by the total word frequency of the annual report. This AI-related word density serves as a proxy variable for the degree of AI technology attention and penetration at the firm level.

(2) Government green funding subsidy (Green_Subsidy) is measured by the natural logarithm of the total green and low-carbon-related government subsidies received by

the firm in the current year. To ensure the economic meaningfulness of the indicator, the natural logarithm is taken after adding 1 to the original amount.

4.2.4. Control Variables

To control for other factors that may affect corporate carbon emission reduction performance, the following firm-level control variables are introduced: Firm size (Size), measured by the natural logarithm of total assets; leverage ratio (Lev); return on assets (ROA), reflects profitability; Tobin's Q (TobinQ), reflects growth potential; fixed asset ratio (FixedAsset); board size (Board); independent director ratio (Indep); and ownership concentration (Top1), measured by the shareholding proportion of the largest shareholder; in addition, industry (Industry) and year (Year) fixed effects are controlled for in the model.

4.2.5. Moderating Variables

Firm ownership type (SOE) takes a value of 1 for state-owned enterprises and 0 otherwise. Industry technological attribute (HighTech) is assigned based on the Administrative Measures for the Recognition of High-tech Enterprises and the CSRC industry classification, where firms in high-technology industries are coded as 1 and 0 otherwise. Regional digital economy development level (Digital_Level) is matched to the provincial-level digital economy development index for the province where the firm's registered address is located. This variable is tested using either a continuous variable or a median split grouping approach (high group = 1, low group = 0).

4.3. Model Specification

4.3.1. Baseline Regression Model (Testing H1)

To test H1, the direct effect of GGP on corporate carbon emission reduction performance, this study follows the research approaches of Cheng et al. to construct the following two-way fixed effects regression model [56].

$$CRP_\{i,t\} = \alpha_0 + \alpha_1 \cdot GGP_\{i,t\} + \Sigma\gamma_k \cdot Controls_\{k,i,t\} + \mu_j + \lambda_t + \varepsilon_\{i,t\} \quad (1)$$

Here, the subscripts i, j, and t denote firm, industry, and year, respectively. The dependent variable CRP_{i,t} represents the carbon emission reduction performance of firm i in year t. The key independent variable GGP_{i,t} is measured using both the dummy variable (GGP_Dum) and the continuous variable (GGP_Ratio). Controls_{k,i,t} represents the kth firm-level control variable vector, including firm size (Size), leverage ratio (Lev), return on assets (ROA), Tobin's Q (TobinQ), fixed asset ratio (FixedAsset), board size (Board), independent director ratio (Indep), and ownership concentration (Top1). μ_j and λ_t represent industry fixed effects and year fixed effects, respectively, controlling for time-invariant industry heterogeneity and firm-invariant macroeconomic shocks. ε_{i,t} is the random error term. If the estimate of α_1 in Model (1) is significantly positive, H1 is supported.

4.3.2. Mediation Effect Model (Testing H2a and H2b)

To test H2a and H2b, the mediating transmission mechanisms of AI penetration rate and government green funding subsidies between GGP and corporate carbon emission reduction, this study follows the causal steps approach proposed by Baron and Kenny and combines it with the nonparametric percentile Bootstrap method (5000 replications) for testing the significance of mediation effects [11]. Building on Model (1), the following two sets of equations are further constructed.

Step 1. Testing the effect of GGP on the mediating variable.

$$M_\{i,t\} = \beta_0 + \beta_1 \cdot GGP_\{i,t\} + \Sigma\gamma_k \cdot Controls_\{k,i,t\} + \mu_j + \lambda_t + \varepsilon_\{i,t\} \quad (2)$$

Step 2. Simultaneously including the key independent variable and the mediating variable in the baseline model.

$$CRP_\{i,t\} = c_0 + c_1 \cdot GGP_\{i,t\} + c_2 \cdot M_\{i,t\} + \Sigma\gamma_k \cdot Controls_\{k,i,t\} + \mu_j + \lambda_t + \varepsilon_\{i,t\} \quad (3)$$

Here, M_{i,t} represents the two mediating variables, namely (i) AI penetration rate AI_Penetration_{i,t}, measured as the word frequency ratio of AI-related terms in annual reports, and (ii) government green funding subsidy Green_Subsidy_{i,t}, measured as the natural logarithm of the firm's green subsidy amount plus 1 in the current year. If β_1 in Equation (2) and c_2 in Equation (3) are both significant, and the Bootstrap-tested indirect effect $\beta_1 \times c_2$ has a confidence interval that does not contain zero, the mediation effect is established. If c_1 in Equation (3) remains significant, the mediation is partial; if c_1 is not significant, the mediation is complete.

Furthermore, to test the synergistic reinforcement effect between the two mediation pathways described in H3, the following interaction term model is constructed.

$$\begin{aligned} CRP_\{i,t\} = {} & \varphi_0 + \varphi_1\, GGP_\{i,t\} + \varphi_2\, AI_\{i,t\} + \varphi_3\, Subsidy_\{i,t\} + \varphi_4\, (AI \times Subsidy)_\{i,t\} + \varphi_5\, (GGP \times AI)_\{i,t\} + \\ & \varphi_6\, (GGP \times Subsidy)_\{i,t\} + \Sigma\, \gamma_k\, Controls_\{k,i,t\} + \mu_j + \lambda_t + \varepsilon_\{i,t\} \end{aligned} \quad (4)$$

This model includes the interaction terms between green procurement and each mediating variable, as well as the interaction term between AI penetration and green subsidies. If the interaction term coefficient φ_4, φ_5, φ_6 is significantly positive, it indicates that AI large model penetration rate and government green funding subsidies exhibit a positive synergistic effect in promoting corporate carbon emission reduction, thereby supporting H3. To mitigate potential multicollinearity introduced by the interaction term, AI_Penetration and Green_Subsidy are mean-centred before entering the interaction term.

4.3.3. Heterogeneity Analysis Model

To test the heterogeneity of the impact of GGP on corporate carbon emission reduction (H4a, H4b, H4c), this study employs a subsample regression approach. The sample is divided into different subsamples according to firm ownership type (SOE vs. non-SOE), industry technological attribute (high-technology industry vs. non-high-technology industry), and the digital economy development level of the firm's region (high-level group vs. low-level group, divided at the median of the provincial digital economy development index). Model (1) is estimated within each subsample, and Fisher's permutation test (1000 replications) is used to compare whether the differences in the coefficients of the key independent variable GGP across subsamples are statistically significant. Specifically, the subsample model is specified as follows.

$$CRP_\{i,t\} \mid G = g = \alpha_0{}^{g} + \alpha_1{}^{g} \cdot GGP_\{i,t\} + \Sigma\gamma_k{}^{g} \cdot Controls_\{k,i,t\} + \mu_j + \lambda_t + \varepsilon_\{i,t\} \quad (5)$$

Here, G denotes the grouping variable, and $g \in \{0, 1\}$. If $\alpha_1{}^{1}$ is significantly larger than $\alpha_1{}^{0}$ (and the between-group coefficient difference passes the Fisher test), heterogeneity is confirmed along that dimension. As a robustness supplement, this study also employs a full sample interaction term model for cross-validation.

$$CRP_\{i,t\} = \psi_0 + \psi_1 \cdot GGP_\{i,t\} + \psi_2 \cdot G_\{i,t\} + \psi_3 \cdot (GGP_\{i,t\} \times G_\{i,t\}) + \Sigma\gamma_k \cdot Controls_\{k,i,t\} + \mu_j + \lambda_t + \varepsilon_\{i,t\} \quad (6)$$

If the interaction term coefficient ψ_3 is significant, it further validates the conclusions from the subsample regressions. The grouping variable G takes values of SOE (state- owned enterprise = 1, otherwise = 0), HighTech (high-technology industry = 1, otherwise = 0), and Digital_High (digital economy development index above the annual sample median = 1, otherwise = 0).

5. Results and Analysis

5.1. Descriptive Statistics and Correlation Analysis

Table 1 reports the descriptive statistics for the main variables. The mean of corporate carbon emission reduction performance (CRP) is 5.824 with a standard deviation of 3.142, a minimum of 0.408, and a maximum of 18.973, indicating some variation in carbon emission efficiency across firms. The mean of the GGP dummy variable (GGP_Dum) is 0.187, suggesting that approximately 18.7% of firms obtained government green procurement contracts during the sample period. The mean of the continuous variable (GGP_Ratio) is 0.0234, indicating that green procurement contract amounts account for approximately 2.34% of firm revenue on average. However, the maximum reaches 0.5124 (i.e., 51.24%), suggesting that some firms exhibit a certain degree of dependence on the government green procurement market. The mediating variable AI penetration rate (AI_Penetration), expressed in per mille, has a mean of 1.526 and a standard deviation of 2.894 with a maximum of 34.215, reflecting some differentiation among sample firms in terms of AI technology attention and application. The government green funding subsidy (Green_Subsidy) has a mean of 7.823 and a standard deviation of 5.246, indicating that a considerable proportion of firms did not receive dedicated green subsidies (with a lower bound of 0), while among those that did, subsidy amounts vary substantially.

Table 1. Descriptive statistics of main variables.

Variable	N	Mean	S.D.	Min	Median	Max
CRP	13,246	5.824	3.142	0.408	5.312	18.973
GGP_Dum	13,246	0.187	0.390	0.000	0.000	1.000
GGP_Ratio	13,246	0.0234	0.0716	0.000	0.000	0.5124
AI_Penetration (‰)	13,246	1.526	2.894	0.000	0.437	34.215
Green_Subsidy	13,246	7.823	5.246	0.000	9.124	19.235
Size (ln assets)	13,246	22.347	1.398	19.756	22.184	26.584
Lev	13,246	0.442	0.203	0.062	0.436	0.928
ROA	13,246	0.038	0.075	−0.285	0.042	0.251
TobinQ	13,246	2.127	1.486	0.853	1.674	9.347
FixedAsset	13,246	0.218	0.163	0.002	0.184	0.721
Board (ln)	13,246	2.142	0.194	1.609	2.197	2.708
Indep	13,246	0.376	0.053	0.333	0.364	0.571
Top1	13,246	0.341	0.149	0.082	0.323	0.758
SOE	13,246	0.352	0.478	0.000	0.000	1.000
HighTech	13,246	0.434	0.496	0.000	0.000	1.000
Digital_Level	13,246	0.512	0.184	0.132	0.526	0.894

Table 2 reports the correlation matrix; both GGP_Dum and GGP_Ratio are significantly positively correlated with CRP at the 1% level (Pearson r = 0.093 and 0.062; Spearman ρ = 0.092 and 0.090), providing preliminary support for H1. The mediating variables AI_Penetration and Green_Subsidy are also positively correlated with CRP, and both are significantly correlated with the key independent variables, offering initial evidence consistent with the proposed mediation pathways. The correlation between GGP_Dum and Green_Subsidy is relatively high (Pearson r = 0.844), reflecting that firms obtaining government green procurement contracts are more likely to receive dedicated green subsidies, which is consistent with the theoretical expectation of the financial provision pathway.

Table 2. Correlation matrix of main variables.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) CRP	1.000	0.092 ***	0.090 ***	0.020 **	0.071 ***	0.335 ***	−0.055 ***	0.066 ***	0.065 ***	0.015 *	0.008	0.013	0.016 *
(2) GGP_Dum	0.093 ***	1.000	0.988 ***	0.233 ***	0.761 ***	0.098 ***	0.014	0.021 **	−0.011	0.009	0.002	−0.017 **	−0.015 *
(3) GGP_Ratio	0.062 ***	0.670 ***	1.000	0.231 ***	0.752 ***	0.098 ***	0.017 *	0.022 **	−0.011	0.009	−0.001	−0.017 **	−0.015 *
(4) AI_Pen.	0.013	0.207 ***	0.139 ***	1.000	0.172 ***	0.014	0.007	0.012	−0.006	0.001	−0.004	0.005	0.002
(5) Green_Sub.	0.082 ***	0.844 ***	0.567 ***	0.174 ***	1.000	0.071 ***	0.006	0.013	−0.013	0.002	0.003	−0.008	−0.020 **
(6) Size	0.344 ***	0.102 ***	0.069 ***	0.012	0.082 ***	1.000	0.102 ***	−0.009	0.007	0.113 ***	−0.003	0.007	0.018 **
(7) Lev	−0.058 ***	0.015 *	0.023 ***	−0.002	0.013	0.108 ***	1.000	−0.159 ***	0.004	0.007	0.008	0.009	0.006
(8) ROA	0.071 ***	0.018 **	0.014 *	0.007	0.014	−0.014	−0.168 ***	1.000	0.016 *	−0.006	−0.012	−0.007	0.005
(9) TobinQ	0.062 ***	−0.016 *	−0.012	−0.010	−0.015 *	0.004	0.003	0.015 *	1.000	0.002	−0.017 *	0.009	−0.015 *
(10) FixedAsset	0.013	0.008	0.010	0.000	0.008	0.116 ***	0.006	−0.002	0.004	1.000	−0.001	0.009	−0.007
(11) Board	0.013	0.001	−0.006	−0.010	0.004	−0.003	0.010	−0.013	−0.018 **	−0.003	1.000	−0.014	0.009
(12) Indep	0.017 *	−0.016 *	−0.013	0.002	−0.009	0.007	0.009	−0.010	0.008	0.009	−0.014	1.000	−0.001
(13) Top1	0.018 **	−0.015 *	−0.015 *	0.003	−0.020 **	0.017 *	0.005	0.008	−0.015 *	−0.008	0.005	0.002	1.000

Notes. Pearson correlation coefficients are reported below the diagonal; Spearman rank correlation coefficients are reported above the diagonal. Column headings (1) to (13) correspond to the variables listed in the first column. N = 13,246. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

To further assess potential multicollinearity, the variance inflation factor (VIF) test is conducted for the baseline regression and the full model, including the mediating variables. The results are reported in Table 3. In the baseline specification with GGP_Dum, all VIF values are below 1.05, with a mean VIF of 1.015, indicating negligible multicollinearity among the regressors. The baseline specification with GGP_Ratio yields similar results (mean VIF = 1.014). In the full model incorporating both mediating variables, the highest VIF is 3.540 (for GGP_Dum), and the mean VIF is 1.472. All VIF values remain well below the conventional threshold of 10 (and even below the more stringent threshold of 5), confirming that the estimation results are not distorted by severe multicollinearity.

Table 3. Variance inflation factor (VIF) test results.

Variable	Model (1) VIF	Model (1) 1/VIF	Model (2) VIF	Model (2) 1/VIF	Model (3) VIF
GGP_Dum	1.012	0.988	—	—	3.540
GGP_Ratio	—	—	1.006	0.994	—
AI_Penetration	—	—	—	—	1.045
Green_Subsidy	—	—	—	—	3.482
Size	1.037	0.965	1.031	0.970	1.037
Lev	1.041	0.960	1.042	0.960	1.041
ROA	1.030	0.971	1.030	0.971	1.030
TobinQ	1.001	0.999	1.001	0.999	1.001
FixedAsset	1.014	0.986	1.014	0.986	1.014
Board	1.001	0.999	1.001	0.999	1.001
Indep	1.001	0.999	1.001	0.999	1.001
Top1	1.001	0.999	1.001	0.999	1.001
Mean VIF	1.015	—	1.014	—	1.472
Max VIF	1.041	—	1.042	—	3.540

Notes. Model (1) refers to the baseline regression with GGP_Dum as the key independent variable. Model (2) refers to the baseline regression with GGP_Ratio as the key independent variable. Model (3) is the full specification including both mediating variables (AI_Penetration and Green_Subsidy) together with the baseline independent variable (GGP_Dum) and all controls.

5.2. Baseline Regression Results

To test H1, the promoting effect of GGP on corporate carbon emission reduction performance, this study employs a two-way fixed effects model for regression analysis. The results are presented in Table 4. Columns (1) and (2) report the regression results with GGP_Dum and GGP_Ratio as the key independent variables, respectively. The results show that the coefficients of GGP are significantly positive at the 1% level regardless of whether the dummy or continuous variable is used. These results confirm H1, indicating a significant positive correlation between access to government green procurement contracts and corporate carbon emission reduction, with such an association operating indirectly through multiple mechanisms. Specifically, firms awarded government green procurement contracts exhibit higher average carbon productivity, and as the scale of green procurement expands, firms achieve better carbon emission reduction outcomes. In terms of underlying mechanisms, on the one hand, government green procurement, as a formal institutional arrangement, imposes compliance pressure on firms, prompting them to optimise production processes and improve energy use efficiency to meet green procurement criteria. On the other hand, it sends clear green development signals to the market, incentivising firms to invest more in artificial intelligence and other digital technologies to enhance carbon reduction efficiency through technological empowerment, thereby improving carbon productivity. These findings align with the predictions of institutional theory and signalling theory. By implementing green procurement policies, governments shape the institutional context for corporate green development and compel firms to standardise their environmental behaviours. Meanwhile, government green procurement conveys positive

signals regarding firms' environmental performance to the market, helping firms acquire more market resources and motivating continuous investment in green transition to boost carbon reduction performance.

Table 4. Baseline regression results of GGP on corporate carbon emission reduction performance.

Variable	(1) CRP	(2) CRP
GGP_Dum	0.2834 *** (5.67)	—
GGP_Ratio	—	1.8675 *** (4.93)
Size	0.9247 *** (11.24)	0.9318 *** (11.31)
Lev	−1.2417 *** (−6.87)	−1.2385 *** (−6.82)
ROA	2.1843 *** (3.56)	2.1732 *** (3.54)
TobinQ	0.1238 *** (4.23)	0.1241 *** (4.25)
FixedAsset	−0.5832 ** (−2.14)	−0.5798 ** (−2.12)
Board	0.3124 * (1.87)	0.3143 * (1.89)
Indep	0.8452 ** (2.04)	0.8476 ** (2.05)
Top1	0.2183 (1.23)	0.2195 (1.24)
Constant	−15.2340 *** (−8.67)	−15.3120 *** (−8.71)
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	13,246	13,246
R^2_within	0.246	0.243
F statistic	42.87 ***	38.64 ***

Notes. *t*-statistics based on firm-level clustered robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Column (1) uses the dummy variable GGP_Dum; Column (2) uses the continuous variable GGP_Ratio.

5.3. Mediation Effect Test Results

To test the digital empowerment pathway (H2a) and the financial provision pathway (H2b), this study employs the Bootstrap method for mediation effect testing. The results are presented in Table 5.

Table 5. Synergy model and marginal effects of green funding at different AI penetration levels.

Variable	(1) CRP Synergy Model	(2) Coefficient	(3) *t*-Statistic
Panel A. Synergy Regression (Dependent Variable = CRP)			
GGP_Dum	0.1842 *** (3.74)	0.1842	3.74
AI_Penetration	0.0118 *** (3.21)	0.0118	3.21
Green_Subsidy	0.0193 *** (4.45)	0.0193	4.45
AI × Subsidy	0.00074 ** (2.18)	0.00074	2.18
GGP × AI	0.0526 ** (2.47)	0.0526	2.47
GGP × Subsidy	0.0341 * (1.89)	0.0341	1.89
Controls	Yes	Yes	Yes
Industry/Year FE	Yes	Yes	Yes
N	13,246	13,246	13,246
R^2	0.273	—	—
Panel B. Marginal Effect of Green_Subsidy on CRP at Different Percentiles of AI_Penetration			
AI_Penetration Percentile	Marginal Effect	Standard Error	95% Confidence Interval
25th percentile (AI = 0.392)	0.0162 **	0.0067	[0.0031, 0.0293]
50th percentile (AI = 0.804)	0.0193 ***	0.0044	[0.0107, 0.0279]
75th percentile (AI = 1.736)	0.0241 ***	0.0058	[0.0127, 0.0355]
Difference (75th−25th)	0.0079 *	0.0044	[0.00006, 0.0158]

Notes. *t*-statistics based on firm-level clustered robust standard errors are reported in parentheses in Panel A. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. In Panel A, AI_Penetration and Green_Subsidy are mean-centred, and the three interaction terms are constructed from centred components. In Panel B, the marginal effect of Green_Subsidy is computed as $\varphi_3 + \varphi_4 \times$ AI_centred at the sample 25th, 50th, and 75th percentiles of AI_Penetration. Standard errors and 95% confidence intervals are obtained via the delta method with 1000 Bootstrap replications. The monotonically rising marginal effect across the three percentiles demonstrates the practical magnitude of the synergy.

Mediation by AI Penetration Rate (H2a)

Results in Panel A of Table 5 reveal the core transmission mechanism through which government green procurement affects corporate carbon reduction performance. The first-stage regression shows that government green procurement (GGP_Dum) exerts a significantly positive effect on AI penetration (AI_Penetration). From the perspectives of institutional theory and signalling theory, as a formal institutional arrangement, green procurement imposes compliance pressure that compels firms to pursue technological upgrading, while releasing green market signals to reduce uncertainties in digital transformation and motivate AI adoption. The second-stage regression further indicates that AI penetration is positively associated with carbon reduction performance (CRP), verifying the logic of digital empowerment. Leveraging advantages in data processing and intelligent monitoring, AI enables precise carbon emission management and energy allocation optimisation, thereby improving emission reduction efficiency. Bootstrap tests confirm that AI penetration plays a partial mediating role. Specifically, government green procurement promotes corporate carbon reduction both directly via institutional constraints and signalling incentives, and indirectly by facilitating digital transformation. Theoretically, this identified mechanism enriches research on government green procurement and corporate environmental behaviour, provides new empirical evidence for institutional and signalling theories, and advances the understanding of interactions between the digital economy and corporate green development, highlighting the emission-reduction value of policy–technology synergy.

Mediation by Government Green Funding Subsidy (H2b)

The results in Panel B of Table 5 show that Government green procurement (GGP_Dum) increases firms' likelihood of obtaining green subsidies (Green_Subsidy). Essentially, green procurement serves as official credit endorsement: by winning green procurement contracts, firms signal strong environmental compliance and credible green projects to governmental authorities, which enhances their policy recognition and facilitates access to targeted fiscal support in subsequent subsidy applications (first-stage regression). Green subsidies exert a positive effect on corporate carbon reduction performance (CRP). From the resource dependence theory perspective, green transition involves substantial investment in R&D, equipment upgrading and low-carbon renovation. Green subsidies directly ease financing constraints, provide stable financial support for low-carbon technology development and energy saving retrofits, and compensate for resource shortages in corporate green development (second-stage regression). Bootstrap tests verify the significant mediating role of green subsidies, thereby validating Hypothesis H2b. This mechanism forms a complete transmission chain: government green procurement policy signalling endorsement green financial support improved carbon reduction performance. Theoretically, it extends the application of signalling theory to fiscal policy coordination and confirms that demand-side government policies can empower corporate low-carbon transition by leveraging supply- side fiscal resources from the resource dependence perspective.

Comparison of Dual Pathways and Synergy

Column (1) of Table 5 presents the synergy effect model. The interaction term of AI penetration and green subsidies remains significantly positive at the 5% level, verifying robust synergy effects. The interaction terms of GGP AI and GG Green Subsidy are significantly positive at the 5% and 10% levels respectively, implying that government green procurement amplifies the carbon reduction effects of AI penetration and green finance, with a stronger reinforcement on the AI channel. Meanwhile, the direct effect of GGP is significantly positive, suggesting its independent carbon reduction effect and channel specific amplification effect. Thus, the baseline synergy estimates are free from

omitted variable bias. Following Brambor et al., we calculate the marginal effects of green subsidies on CRP at the 25th, 50th and 75th percentiles of AI penetration, using the formula [57]:

$$\partial \mathrm{CRP}/\partial \mathrm{Subsidy} = \varphi_3 + \varphi_4 \times \mathrm{AI_centred}$$

where AI_centred denotes AI_Penetration measured in deviations from its sample mean.

Column (2) of Panel B in Table 5 shows that the marginal effects are 0.0162 (5% significance), 0.0193 (1% significance), and 0.0241 (1% significance) at the three percentiles, respectively. During the 14th Five-Year Plan period, China's digital economy has shifted from infrastructure construction to deep industrial integration. AI penetration not only directly promotes corporate green procurement (CRP) but also amplifies the policy effect of green subsidies through the interaction term AI × Subsidy (coefficient 0.00074, $t = 2.18$). Marginal effect analysis shows that in high-AI-penetration regions (75th percentile), the marginal effect of subsidies (0.0241) is about 49% higher than in low-AI-penetration regions (25th percentile, 0.0162), and the difference is significant. This indicates that digital technology, by optimising resource allocation, reducing information asymmetry and enhancing carbon footprint verification capabilities, generates a multiplier effect of technology empowerment × green incentives, making the digital empowerment pathway relatively more critical in the sample. Compared with traditional financial subsidies, digital technologies can markedly improve policy implementation efficiency and carbon abatement outcomes by optimising resource allocation, reducing deviations in policy enforcement and accurately identifying emission reduction potential. They have gradually gone beyond the logic of simple fiscal support and become an important vehicle for unlocking policy dividends and achieving long-term emission cuts. Accordingly, future policy design should further integrate policy incentives with digital technologies, and guide enterprises to fully tap the emission reduction potential of green public procurement through intelligent transformation.

The marginal effect at the 75th percentile is 1.49 times that at the 25th percentile, confirming Hypothesis H3 that green subsidies yield higher carbon reduction returns for firms with higher AI penetration. This highlights that integrating green finance subsidies with AI capacity investment maximises marginal environmental benefits.

5.4. Heterogeneity Analysis Results

To further examine the boundary conditions of the GGP policy effect, this study conducts subsample regression tests. The results are presented in Table 6.

Heterogeneity by Firm Ownership Type (H4a)

As shown in Columns (1) and (2) of Table 6, the coefficient of government green procurement (GGP_Dum) is larger and more significant in the state-owned enterprise (SOE) subsample, verifying Hypothesis H4a that green procurement exerts a stronger carbon reduction effect on SOEs than on non-SOEs. Drawing on property rights theory and institutional theory, this heterogeneity stems from the inherent ownership characteristics of SOEs. As key agents for implementing governmental environmental policies, SOEs maintain natural institutional linkages with the government. They bear greater environmental responsibilities and respond more proactively to green procurement policies, while enjoying preferential access to state resources that underpin emission reduction activities and amplify policy incentives. These findings reveal the heterogeneous transmission of policy effects across ownership types, extend the theoretical application of relevant frameworks, and provide implications for designing differentiated green policies.

Table 6. Heterogeneity analysis results (subsample regressions).

Variable	(1) SOE	(2) Non-SOE	(3) HighTech	(4) Non-HT	(5) High DL	(6) Low DL
GGP_Dum	0.3847 *** (4.92)	0.1983 ** (2.34)	0.4256 *** (5.43)	0.1534 ** (2.17)	0.4092 *** (5.18)	0.1287 * (1.88)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4663	8583	5749	7497	6621	6625
R^2_within	0.271	0.234	0.283	0.221	0.276	0.218
Fisher *p*	0.024	—	0.008	—	0.013	—

Notes. *t*-statistics based on clustered robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The dependent variable is CRP. Fisher between group *p*-values are based on 1000 Bootstrap permutation tests to assess the statistical significance of the between group difference in GGP_Dum coefficients.

Heterogeneity by Industry Technological Attribute (H4b)

As shown in Columns (3) and (4) of Table 6, government green procurement generates a stronger carbon reduction effect for firms in high-tech industries, verifying Hypothesis H4b. From the perspective of the resource-based view, such heterogeneity originates from the core technological endowments of high-tech enterprises. Equipped with superior technological innovation and absorption capabilities, these firms can rapidly respond to demand side signals from green procurement, translate policy incentives into low-carbon technological solutions, and achieve emission reduction upgrades efficiently via digital technologies such as artificial intelligence. These findings uncover the moderating role of technological capacity in policy transmission, highlight the synergistic value between policy incentives and firm-level technological foundations, and provide evidence for the formulation of differentiated environmental policies.

Heterogeneity by Regional Digital Economy Development Level (H4c)

As shown in Columns (5) and (6) of Table 6, the carbon reduction effect of government green procurement is significantly stronger in regions with a high level of digital economy development, which verifies Hypothesis H4c. From the perspective of institutional theory, regional digital development serves as an external enabling condition for corporate green transition. Regions with advanced digital economies feature sound digital infrastructure, mature data factor markets and abundant digital talent pools, which effectively reduce the costs and barriers for firms to adopt low-carbon digital technologies such as artificial intelligence. In such favourable environments, policy signals released by green procurement can be better implemented. Firms can readily leverage external digital resources to conduct emission reduction practices including intelligent management and energy optimisation, thereby amplifying the carbon reduction effect of green procurement through digital pathways. These findings identify the boundary conditions of regional external environments for policy transmission, reflect the synergies between policy incentives and regional digital endowments, and provide theoretical and empirical evidence for implementing targeted green procurement policies and optimising regional digital supporting systems.

To further examine whether the relative importance of the two channels differs across subgroups, this study conducts mediation effect analyses within each subsample. The results are presented in Table 7.

The results show that the indirect effect and mediating ratio of the subsidy channel are significantly higher for state-owned enterprises (SOEs) than for non-SOEs (0.0578, 15.03% vs. 0.0214, 10.79%, $p = 0.012$), whereas the difference in the AI channel is insignificant ($p = 0.214$). This indicates that SOE's policy advantages stem from easier access to green subsidies rather than superior AI application capabilities. The indirect effect of the AI channel is significantly stronger for high-tech firms than for non-high-tech firms (0.0612,

14.38% vs. 0.0263, 17.14%, p = 0.004), while the subsidy channel shows no significant intergroup difference (p = 0.612). This suggests that high-tech firms benefit from digital empowerment driven by technological absorption capacity, rather than preferential access to green finance. Digitalised regions exhibit a significantly larger indirect effect via the AI channel than those in less digitalised regions (0.0563, 13.76% vs. 0.0207, 16.08%, p = 0.019), with no significant difference observed in the subsidy channel (p = 0.781), confirming that regional heterogeneity arises mainly from the digital empowerment pathway. Accordingly, the relative importance of the two mediating channels is heterogeneous across contexts: SOEs gain advantages primarily through the financial support channel, whereas high-tech firms and those in highly digitalised regions rely more on digital empowerment. This dual-channel framework provides a structural explanation for the heterogeneous emission reduction effects of government green procurement (GGP), beyond simple differences in policy sensitivity.

Table 7. Subsample mediation test results.

Variable	(1) SOE	(2) Non-SOE	(3) HighTech	(4) Non-HT	(5) High DL	(6) Low DL
Panel A. (GGP → AI_Penetration → CRP)						
GGP → AI (β_1)	2.6432 *** (3.87)	2.9214 *** (4.36)	3.4815 *** (4.92)	1.9876 *** (2.83)	3.1247 *** (4.51)	2.0438 *** (2.94)
AI → CRP (c_2)	0.0174 *** (3.42)	0.0131 *** (3.05)	0.0176 *** (3.78)	0.0132 *** (2.84)	0.0180 *** (3.69)	0.0101 ** (2.51)
Indirect Effect	0.0461 ***	0.0382 ***	0.0612 ***	0.0263 ***	0.0563 ***	0.0207 **
95% Bootstrap CI	[0.0231, 0.0703]	[0.0186, 0.0594]	[0.0327, 0.0917]	[0.0098, 0.0438]	[0.0298, 0.0848]	[0.0046, 0.0382]
Mediation Proportion (%)	11.99	19.27	14.38	17.14	13.76	16.08
AI → CRP (c_2)	0.0174 *** (3.42)	0.0131 *** (3.05)	0.0176 *** (3.78)	0.0132 *** (2.84)	0.0180 *** (3.69)	0.0101 ** (2.51)
Z test on Difference (p)	0.214 (vs. Non-SOE)	—	0.004 *** (vs. Non-HT)	—	0.019 ** (vs. Low DL)	—
Panel B. Subsidy Pathway Mediation (GGP → Green_Subsidy → CRP)						
GGP → Subsidy (β_1)	2.4218 *** (10.34)	1.0837 *** (6.78)	1.5631 *** (8.42)	1.3946 *** (7.61)	1.4827 *** (8.83)	1.4316 *** (7.92)
Subsidy → CRP (c_2)	0.0239 *** (4.83)	0.0198 *** (4.21)	0.0209 *** (4.36)	0.0209 *** (4.31)	0.0201 *** (4.24)	0.0191 *** (4.05)
Indirect Effect	0.0578 ***	0.0214 ***	0.0327 ***	0.0291 ***	0.0298 ***	0.0274 ***
95% Bootstrap CI	[0.0316, 0.0867]	[0.0093, 0.0354]	[0.0162, 0.0518]	[0.0143, 0.0461]	[0.0146, 0.0476]	[0.0128, 0.0451]
Mediation Proportion (%)	15.03	10.79	7.69	18.97	7.28	21.29
Z-test on Difference (p)	0.012 ** (vs. Non-SOE)	—	0.612 (vs. Non-HT)	—	0.781 (vs. Low DL)	—
N	4663	8583	5749	7497	6621	6625

Notes. t-statistics based on firm-level clustered robust standard errors are reported in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively.

5.5. Endogeneity Treatment and Causal Identification

Given the nonrandom nature of GGP policy, firms with better carbon emission reduction performance may be more likely to be selected by the government. Unobserved firm characteristics (such as executive environmental awareness, political connections, and social responsibility orientation) may simultaneously influence GGP opportunities and carbon emission reduction performance. Thus, the baseline model estimates may suffer from endogeneity problems including reverse causality, omitted variable bias, and sample self-selection. To address these concerns, this study employs three identification strategies for systematic examination, namely the instrumental variable method, the Heckman two-stage model, and propensity score matching with difference in differences (PSM-DID).

5.5.1. Instrumental Variable Method (IV-2SLS)

Following the approaches of Nunn and Qian and Goldsmith Pinkham et al., this study constructs a dual instrumental variable system [58,59]. First, the historical instrumental variable (GGP_Hist) is the logarithmic mean of the prefecture-level city's government green procurement scale from 2015 to 2019, reflecting the path dependence of local government procurement preferences. It satisfies the relevance condition while satisfying the exclusion restriction through the intergenerational transmission of regional traditions that indirectly influence current-period decisions. Second, the shift share geographic instrumental variable (Dist_IV) is the interaction between the inverse of the distance from the firm's registered address to the nearest free trade zone and the current year's national total government procurement amount, where the distance component is time invariant and the scale component captures macroeconomic shocks.

Table 8 reports the IV-2SLS estimation results. Columns (1) and (3) present the first-stage regressions, where both instrumental variables have coefficients that are significantly positive at the 1% level for GGP_Dum and GGP_Ratio, indicating strong relevance. Weak instrument tests show that the Kleibergen Paap rk Wald F statistics are 84.56 and 76.12, respectively, both far exceeding the Stock Yogo critical value of 19.93 at 10% maximal relative bias, rejecting the weak instrument hypothesis. The underidentification test Kleibergen Paap rk LM statistics are significant at the 1% level, rejecting the underidentification hypothesis. The Hansen J statistics yield *p*-values of 0.143 and 0.172, so the instrument exogeneity assumption is not rejected. These three tests collectively confirm the validity of the instrumental variable selection. Columns (2) and (4) present the second-stage regressions, where the IV estimates of GGP_Dum and GGP_Ratio are 0.3416 (t = 4.89) and 2.1432 (t = 4.23), respectively, both significantly positive at the 1% level and slightly larger than the baseline OLS estimates (0.2834 and 1.8675). This indicates that the original estimates indeed exhibit a downward bias, and the carbon reduction effect of GGP becomes even more significant after accounting for endogeneity, providing robust support for H1.

Table 8. IV-2SLS estimation results.

Variable	(1) 1st Stage GGP_Dum	(2) 2nd Stage CRP	(3) 1st Stage GGP_Ratio	(4) 2nd Stage CRP
GGP_Hist	0.1823 *** (12.46)	—	0.0194 *** (11.87)	—
Dist_IV	0.0847 *** (6.32)	—	0.0052 *** (5.76)	—
GGP_Dum	—	0.3416 *** (4.89)	—	—
GGP_Ratio	—	—	—	2.1432 *** (4.23)
Controls	Yes	Yes	Yes	Yes
Industry/Year FE	Yes	Yes	Yes	Yes
N	13,246	13,246	13,246	13,246
R^2	0.284	0.251	0.279	0.248
K-P rk LM	—	98.42 ***	—	89.37 ***
K-P rk Wald F	—	84.56	—	76.12
Stock-Yogo 10%	—	19.93	—	19.93
Hansen J (p)	—	2.14 (0.143)	—	1.87 (0.172)

Notes. *t*-statistics based on clustered robust standard errors are reported in parentheses. *** indicate significance at the 1% levels.

Since the validity of IV-2SLS estimates hinges on the exclusion restriction, the historical instrumental variable GGP_Hist (prefecture-level green procurement scale from 2015 to 2019) is determined by local fiscal capacity, administrative structure and political cycles, making it exogenous to corporate carbon emission reduction outcomes during 2020–2024. We sequentially control three alternative transmission channels, namely local environmental regulation, industrial structure, and regional marketisation and credit conditions, and the core estimates remain robust, verifying the validity of the exclusion restriction. For the

geographic instrumental variable Dist_IV (transfer-sharing instrument), its distance component is shaped by the historical layout of free trade zones driven by national strategies, while its scale component reflects exogenous national procurement shocks. Dist_IV affects corporate carbon reduction solely through contemporary GGP, and the estimates remain significant after altering the interaction specification, further supporting the exclusion restriction. To provide additional validation, we conduct placebo tests using pre-2020 (2017–2019) corporate carbon reduction performance as the dependent variable. As shown in Table 9, the coefficients of both instruments are statistically insignificant with weak economic magnitudes, and the joint Wald test fails to reject the null hypothesis of zero coefficients, lending empirical support to the exclusion restriction.

Table 9. Falsification test of the instrumental variables on pre-sample carbon emission reduction performance.

Variable	(1) Pre-CRP	(2) Pre-CRP	(3) Pre-CRP	(4) Pre-CRP
GGP_Hist	0.0238 (0.94)	—	0.0214 (0.87)	0.0186 (0.74)
Dist_IV	—	0.0117 (1.04)	0.0103 (0.91)	0.0089 (0.78)
Size	—	—	0.7842 *** (8.93)	0.7768 *** (8.86)
Lev	—	—	−0.9874 *** (−5.43)	−0.9821 *** (−5.40)
ROA	—	—	1.6238 *** (3.12)	1.6184 *** (3.10)
TobinQ	—	—	0.0987 *** (3.41)	0.0982 *** (3.39)
FixedAsset	—	—	−0.4218 * (−1.78)	−0.4203 * (−1.77)
Board	—	—	0.2487 (1.43)	0.2492 (1.44)
Indep	—	—	0.6238 (1.51)	0.6231 (1.51)
Top1	—	—	0.1842 (1.04)	0.1839 (1.03)
Industry FE	Yes	Yes	Yes	No
Industry × Year FE	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes
N	7824	7824	7824	7824
R^2_within	0.038	0.041	0.187	0.213
Joint Wald test (p)	—	—	1.69 (0.428)	1.23 (0.541)

Notes. The sample includes 7824 firm- year observations (2017–2019) of firms in the main 2020–2024 sample. The dependent variable is pre-sample carbon reduction performance, constructed consistently with the main CRP indicator. *t*-statistics with firm-level clustered robust standard errors are in parentheses. * and *** denote significance at the 10% and 1% levels. The joint Wald test examines whether GGP_Hist and Dist_IV coefficients are jointly zero; non-rejection validates the exclusion restriction.

5.5.2. Heckman Two-Stage Selection Model

To correct for potential self-selection bias arising from whether a firm is included in the government green procurement list, this study employs the Heckman two-stage model as a robustness check [60]. The first-stage Probit selection equation uses GGP_Dum as the dependent variable and the prefecture-level historical GGP share as the exclusion restriction, estimating the conditional probability of firm entry into the treatment group and computing the inverse Mills ratio (IMR, λ). The second stage incorporates the IMR as a self-selection correction term into the baseline model.

Table 10 reports the estimation results. Column (1) shows that the exclusion restriction variable (prefecture-level historical GGP share) has a significant positive effect on the probability of firm entry into GGP (coefficient = 0.2134, z = 8.47), and the Wald χ^2 statistic is 487.32, significant at the 1% level, indicating a good overall fit of the Probit model. In Column (2), the outcome equation, the IMR coefficient is −0.4237 (t = −2.18), significant at the 5% level, confirming the presence of self-selection bias (unobserved factors simultaneously influence firm entry into the GGP list and carbon emission reduction performance). After IMR correction, the GGP_Dum coefficient is 0.2653 (t = 5.12), remaining significantly

positive at the 1% level and of similar magnitude to the baseline regression result, indicating that the main conclusions are not substantively affected by self-selection bias.

Table 10. Heckman two-stage selection model estimation results.

Variable	(1) Probit Selection Eq. DV = GGP_Dum	(2) OLS Outcome Eq. DV = CRP
GGP_Dum	—	0.2653 *** (5.12)
IMR (λ)	—	−0.4237 ** (−2.18)
GGP_Hist (excl. restr.)	0.2134 *** (8.47)	—
Size	0.3241 *** (14.67)	0.8924 *** (10.98)
Lev	−0.6584 *** (−5.23)	−1.1982 *** (−6.54)
ROA	1.4372 *** (3.87)	2.0647 *** (3.42)
TobinQ	0.0748 ** (2.56)	0.1187 *** (4.08)
Other controls	Yes	Yes
Industry/Year FE	Yes	Yes
Wald χ^2/F	487.32 ***	41.28 ***
Log likelihood	−4823.65	—
R^2	0.216 (Pseudo)	0.253
N	13,246	13,246

Notes. Column (1) reports *z*-statistics in parentheses; Column (2) reports *t*-statistics based on clustered robust standard errors. ** and *** indicate significance at the 5% and 1% levels, respectively. The significant IMR confirms the presence of self-selection bias.

5.5.3. Propensity Score Matching with Difference in Differences (PSM-DID)

This section treats a firm's first receipt of a government green procurement contract as a quasi-natural experimental shock and constructs a PSM-DID identification strategy. The treatment group consists of firms that obtained GGP contracts during the sample period (N = 2473), and the control group consists of firms that never obtained GGP contracts (N = 10,773). First, a Probit propensity score is estimated using all control variables as covariates. Four matching methods are then employed for robustness comparison, namely 1-to-1 nearest neighbour matching (calliper = 0.02, with replacement), 1 to 4 nearest neighbour matching, Epanechnikov kernel matching (bandwidth = 0.06), and calliper matching (r = 0.05).

Table 11 presents the balance test results. Before matching, the treatment and control groups exhibit significant differences in key covariates including Size, Lev, ROA, and TobinQ (standardised biases generally exceed 10%). After matching, all covariate standardised biases fall below 3%, and all *t*-test *p*-values exceed 0.05, indicating that the treatment and control groups achieve adequate balance in observable characteristics after matching. Table 12 reports the corresponding common support region distribution. Under the common support restriction, only 12 treated firms (0.49% of the treatment group) fall outside the overlap region and are dropped, whereas the remaining 2461 treated firms (99.51%) lie within the common support region and are successfully matched to comparable control firms; on the control side, 10,502 of the 10,773 firms (97.48%) also fall within the common support region. This confirms that virtually all treated samples can find appropriate matching counterparts in the control group, satisfying the common support assumption and ensuring the reliability of the subsequent ATT estimation. Table 13 reports the average treatment effect on the treated (ATT) under the four matching methods. The ATT estimates are approximately 0.27 across all four methods, significant at the 1% level, and consistent with the baseline regression result (0.2834). Furthermore, the event parallel trend test shows that the dynamic treatment effect coefficients for the three pre-treatment periods (pre-3, pre-2, pre-1) are all insignificant (*p*-values of 0.680, 0.708, and 0.471, respectively), not rejecting the parallel trend assumption.

In addition, the dynamic treatment effect event study plot reported in Figure 1 shows that the pretreatment coefficients are small in magnitude and statistically indistinguishable from zero, with confidence intervals fully encompassing zero. This finding offers direct visual support for the parallel trend assumption. Following the initial award of a procurement contract, the treatment effect turns positive and grows steadily, becoming statistically significant in the first post-treatment year and ultimately stabilising at a level consistent with the average treatment effect on the treated, as reported in Table 11. This dynamic pattern indicates that the carbon reduction effect of green procurement does not occur contemporaneously and transiently but accumulates gradually as firms translate procurement signals into sustained technology adoption and mitigation investment.

Table 11. PSM-DID balance test results.

Variable	Treated Mean	Control Mean	Std. Bias (%)	Treated Mean	Control Mean	Std. Bias (%)
	Before matching			After matching		
Size	22.892	22.213	38.4	22.871	22.843	2.1
Lev	0.468	0.434	17.8	0.467	0.464	1.4
ROA	0.042	0.037	8.7	0.042	0.041	0.9
TobinQ	1.967	2.183	−14.6	1.974	1.982	−0.5
FixedAsset	0.237	0.214	14.2	0.236	0.238	−1.2
Indep	0.382	0.375	12.5	0.381	0.380	1.8
Top1	0.358	0.337	14.1	0.356	0.353	2.0

Table 12. PSM-DID common support region distribution.

Group	Off Support	On Support	Total
Treatment group	12 (0.49%)	2461 (99.51%)	2473
Control group	271 (2.52%)	10,502 (97.48%)	10,773
Total	283	12,963	13,246

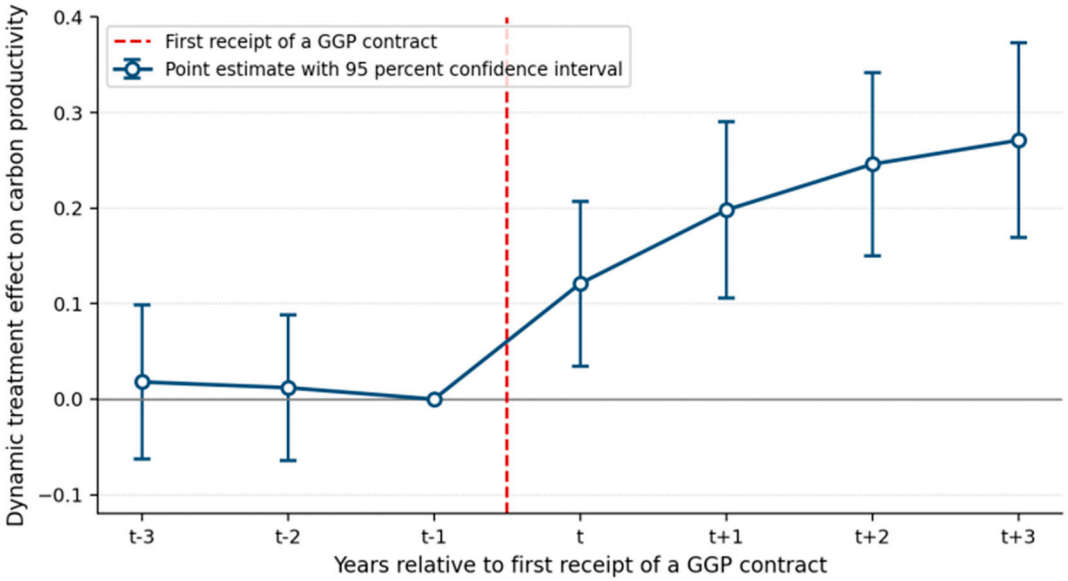


Figure 1. Event study plot of dynamic treatment effects. Note: This event study plot illustrates the dynamic treatment effects of government green procurement on corporate carbon productivity, spanning three years before and three years after firms first receive procurement contracts. Vertical bars denote 95% confidence intervals, with the period immediately before policy implementation taken as the reference period.

Table 13. PSM-DID average treatment effect on the treated (ATT).

Matching Method	ATT	S.E.	*t* Stat.	*p* Value	Matched Obs.
1:1 NN (repl., cal. = 0.02)	0.2689 ***	0.0534	5.03	0.000	12,418
1:4 NN	0.2715 ***	0.0487	5.57	0.000	12,587
Epanechnikov kernel (bw = 0.06)	0.2742 ***	0.0451	6.08	0.000	12,963
matching (r = 0.05)	0.2693 ***	0.0520	5.18	0.000	12,732
Parallel trend Wald test (pre-3 to pre-1)	$\chi^2(3) = 2.34$	$p = 0.505$	—	—	—

Notes. All ATT estimates are computed using 500 Bootstrap replications for standard errors. *** indicate significance at the 1% levels. The parallel trend Wald test does not reject the null hypothesis ($p = 0.505$), indicating no systematic trend difference between the treatment and control groups before policy implementation, thereby validating the PSM-DID identification assumption.

5.6. Robustness Checks

To further validate the robustness of the baseline conclusions, this study conducts robustness checks by replacing the measurement of core variables.

5.6.1. Replacing Core Variables

In Column (1) of Table 14, the dependent variable is replaced with the natural logarithm of carbon emission intensity (CI_ln = ln(CO_2/Revenue)) as a reverse measure of CRP. A lower CI_ln indicates better carbon emission reduction performance, so the coefficient of GGP_Dum should be negative. The results show that the coefficient of GGP_Dum is −0.2483, significant at the 1% level, consistent with the baseline conclusion. In Column (2), CRP is replaced with the Huazheng ESG composite score (a broad-based green performance proxy), and the GGP_Dum coefficient remains significantly positive (0.1964, $p < 0.01$). Column (3) uses "large scale GGP" (GGP_Large, taking a value of 1 when a single contract exceeds 1 million CNY) as an alternative key independent variable, yielding a coefficient of 0.3124, larger than the baseline estimate, suggesting that large-scale contracts produce stronger policy effects. Column (4) uses the natural logarithm of the cumulative GGP scale as a continuous measure, with a coefficient of 0.0047 that is significantly positive. All alternative measures support H1.

Table 14. Robustness checks with alternative variable measures.

Variable	(1) CI_ln (DV)	(2) ESG Score (DV)	(3) GGP_Large (IV)	(4) ln(GGP_Cum.) (IV)
GGP_Dum	−0.2483 *** (−5.01)	0.1964 *** (4.38)	—	—
GGP_Large	—	—	0.3124 *** (4.75)	—
ln(GGP_Cum.)	—	—	—	0.0047 *** (3.89)
Controls	Yes	Yes	Yes	Yes
Industry/Year FE	Yes	Yes	Yes	Yes
N	13,246	11,854	13,246	13,246
R^2	0.283	0.318	0.241	0.237

Notes. *t*-statistics based on clustered robust standard errors are reported in parentheses. *** indicate significance at the 1% levels.

5.6.2. Robustness Check with Objective Measures of AI Penetration

The baseline text frequency-based AI penetration measure may capture managerial attention rather than real technology deployment. To mitigate this concern, we construct three objective firm-level proxies and re-estimate baseline and mediation models.

The three indicators are: (1) AI-related R&D expenditure (AI_RD), the natural logarithm of one plus the share of R&D spending on AI-related projects; (2) digital technology fixed asset investment (Digital_FAI), the natural logarithm of one plus capitalised expenditures on digital hardware, software and infrastructure; and (3) AI and carbon-management

patents (AI_Patent), the natural logarithm of one plus granted invention patents with specific IPC codes.

As shown in Table 15, AI_RD, Digital_FAI and AI_Patent all have significant positive effects on CRP at the 1% level. Mediation tests further confirm that GGP_Dum significantly raises each AI proxy, which in turn improves CRP. Bootstrap indirect effects are significantly non-zero, with mediation proportions (12.3–16.4%) consistent with the text-based result (14.87%). These findings verify that the digital empowerment channel is supported by real-world AI inputs rather than merely textual disclosure.

Table 15. Robustness check using objective measures of AI capability.

Variable	(1) CRP	(2) CRP	(3) CRP	(4) AI_RD	(5) Digital_FAI	(6) AI_Patent
GGP_Dum	0.2671 *** (5.48)	0.2598 *** (5.31)	0.2547 *** (5.19)	0.4825 *** (8.92)	0.5713 *** (9.46)	0.3947 *** (7.83)
AI_RD	0.1247 *** (4.36)	—	—	—	—	—
Digital_FAI	—	0.0938 *** (4.18)	—	—	—	—
AI_Patent	—	—	0.1583 *** (4.74)	—	—	—
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	13,246	13,246	13,246	13,246	13,246	13,246
R^2	0.262	0.258	0.265	0.218	0.247	0.231

Notes. *t*-statistics with firm-level clustered robust standard errors are in parentheses. *** denote significance at the 1% levels. Columns (1)–(3) re-estimate the baseline model using three objective AI proxies. Columns (4)–(6) present the first-stage mediation results, while second-stage estimates (unreported) show significantly positive proxy coefficients at the 1% level. Bootstrap indirect effects (5000 replications) are significant at the 1% level for all three proxies.

5.6.3. Robustness Check Using City-Level Digital Economy Index

The baseline regional heterogeneity analysis matches regional digital economy moderators with provincial-level data, which may mask substantial intra-provincial disparities between cities. To address this issue, we reconduct regional heterogeneity tests using the prefecture-level digital economy index (Digital_City) from the "China Digital Economy City Development Report" jointly released by the China Academy of Information and Communications Technology. Firm-level data are matched with the Digital_City index of the prefecture where firms are registered, and the sample is divided into high and low digital city groups based on the annual median of the Digital_City index. We then re-estimate subsample regressions and the full sample interaction model, with results presented in Table 16. Columns (1) and (2) of Table 16 show that GGP_Dum exerts a significantly positive effect at the 1% level in the high digital city group (coefficient = 0.4287), while only a weak positive effect exists in the low digital city group (coefficient = 0.1184). The Fisher permutation test yields a *p*-value of 0.009, further confirming statistically significant intergroup differences. Column (3) reports the full sample interaction model, where the interaction term between GGP_Dum and high digital city status (Digital_City_High) is significantly positive at the 1% level (coefficient = 0.3142), verifying the moderating role of city-level digital economy development. These city-level findings validate the provincial-level results in Table 6 and reveal more pronounced cross-city disparities. This indicates that intra-provincial heterogeneity is non-negligible, and the digital empowerment channel of GGP works most effectively in cities with mature digital infrastructure and data factor markets, rather than uniformly across all cities within digitally advanced provinces.

Table 16. Regional heterogeneity robustness using city-level digital economy index.

Variable	(1) High Digital_City	(2) Low Digital_City	(3) Full Sample
GGP_Dum	0.4287 *** (5.34)	0.1184 * (1.76)	0.2614 *** (5.32)
Digital_City_High	—	—	0.0428 * (1.93)
GGP_Dum × Digital_City_High	—	—	0.3142 *** (4.07)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	6498	6748	13,246
R^2_within	0.284	0.213	0.258
Fisher p	0.009	—	—

Notes. *t*-statistics based on firm-level clustered robust standard errors are reported in parentheses. * and *** denote significance at the 10% and 1% levels, respectively. Digital_City_High equals 1 if a firm is registered in a prefecture-level city with a Digital_City index above the annual sample median, and 0 otherwise. The Fisher intergroup *p*-value is derived from 1000 Bootstrap permutations. Compared with provincial-level results in Table 6, city-level estimates exhibit more pronounced cross-group coefficient differences, implying that intra-provincial urban digital economic gaps significantly moderate the carbon reduction effect of GGP.

6. Conclusions, Policy Implications, and Future Research

6.1. Research Conclusions

Against the backdrop of the dual carbon goals guiding the deep integration of the digital and green economies, this study integrates institutional theory, signalling theory, and resource dependence theory to construct a framework linking demand incentives with digital empowerment and fiscal provision and ultimately with firm-level decarbonisation performance. Based on the empirical findings, the relevant theoretical framework, and critical reflection, the principal conclusions are summarised as follows.

First, green public procurement can improve corporate carbon emission reduction performance and exerts a notable scale-promoting effect. The baseline results show that access to green procurement contracts and a higher proportion of green procurement contracts both enhance corporate emissions-reduction performance. Theoretically, this study integrates the explanatory logic of institutional theory and signalling theory. It confirms that green public procurement guides the allocation of low-carbon resources in enterprises through the dual effects of institutional pressure and authoritative market signals, and verifies the governance value of market-oriented demand incentive policies. This finding supplements micro-level theoretical evidence on market-based environmental policies and enriches the application of sustainable governance theories in the context of Chinese enterprises. It also provides theoretical support for the transformation of green policies from rigid constraints to market-oriented incentives.

Second, green public procurement promotes corporate carbon reduction via two parallel pathways: digital empowerment and financial support, both of which serve as partial mediators. On one hand, it pushes firms to adopt artificial intelligence and achieve targeted emission cuts through digital and intelligent management, validating the role of digital technology in green governance. On the other hand, it sends positive policy signals to help firms obtain green subsidies and ease financing constraints, which is consistent with the core viewpoints of resource dependence theory. This study makes theoretical contributions by revealing the dual transmission mechanism of technological and financial empowerment in green policies, overcoming the limitation of prior research that focused solely on financial or institutional pathways. It also clarifies the synergistic effects of digital and financial assets and improves the micro-mechanism for integrated digital and green governance.

Third, the carbon reduction effect of green public procurement varies across enterprises and regions. It generates stronger effects for state-owned enterprises, high-tech firms

and those located in regions with a sound digital economy. This finding enriches the theory of context-dependent environmental policy effects, indicating policy outcomes rely heavily on firm resource endowments and regional digital infrastructure. This study also reflects on practical limitations such as uneven policy impacts, greenwashing risks, insufficient supervision and inefficient resource allocation. It defines the applicable scope of relevant policies and addresses the research gap of overemphasising positive effects while ignoring limitations. The results offer references for future theoretical improvement and policy implementation.

6.2. Policy Implications

Drawing on the theoretical contributions, empirical findings, and heterogeneity results of this study together with the pilot practice of GGP reform in China, we put forward actionable and operational policy recommendations along four dimensions, namely top-level design, technological coordination, financial linkage, and precision-targeted measures, to enhance policy specificity and feasibility.

(1) Refining carbon footprint admission and scoring rules for green procurement and reinforcing demand-side rigidity. Government agencies should continue to expand the scale and category coverage of green procurement and transform carbon footprint management from principled requirements into quantifiable institutional rules. Drawing on the experience of domestic pilots in green and low-carbon government procurement, sector-specific carbon footprint rules should be differentiated. For energy-intensive manufacturing, building materials, and chemical industries, full life-cycle carbon footprint compliance should serve as the admission threshold for bidding, excluding non-compliant firms outright and motivating proactive emission reduction. Drawing on existing green and low-carbon product standard systems, sector-specific carbon accounting rules and baseline emission limits should be established to harmonise calculation conventions and reduce corporate compliance costs. Clear market access and scoring mechanisms can compel green transition along the entire value chain.

(2) Promote synergy between green procurement and digital technology policies to create a closed loop of demand pull and technology empowerment. Building upon the digital empowerment mediation mechanism identified in this study, the deployment of AI, big data, and related technologies should be embedded within green procurement institutional design. First, the bidding evaluation system should incorporate dedicated scoring categories for AI-based carbon footprint accounting, intelligent energy scheduling, and digital carbon management platforms, with additional points awarded to firms already operating AI-based carbon control systems. Second, dedicated support should be extended to small and medium-sized enterprises through inclusive AI carbon accounting tools developed jointly by local governments and third-party institutions, with foundational computing resources and accounting templates provided free of charge to lower technological barriers for SME suppliers. Third, in regions with less developed digital economies, priority should be given to deploying new infrastructure for industrial internet, energy consumption monitoring, and carbon emission data collection, to remedy hardware deficits and ensure the effective implementation of the digital empowerment pathway of green procurement.

(3) Optimise green funding mechanisms to achieve procurement-driven investment and coordinated procurement investment linkages. Based on the mediating effect of green financial support, this paper proposes establishing a coordination mechanism linking green public procurement with green subsidies and green credit. First, tie qualification for green subsidies to performance in green public procurement. Subsidies will be

prioritised for firms to upgrade low-carbon technologies, build AI-based carbon accounting systems and advance intelligent emission reduction. Second, take green procurement orders as credit references in bank evaluations. This helps cut financing costs, streamline approval procedures and ease funding pressure for the low-carbon transition. Third, apply differentiated procurement quotas for private enterprises and traditional industries. Supporting subsidies for AI carbon management and financing guarantees will help them overcome resource constraints. These measures will build a long-term governance model where procurement drives investment and the two work in tandem for green development.

(4) Implement differentiated and targeted incentive strategies. In view of the empirical heterogeneities across ownership, industry, and region, differentiated incentive schemes should be implemented. For non-state-owned and traditional industry firms, dedicated green procurement quotas should be reserved, supported by AI-based carbon management tool subsidies and digital transformation financing guarantees, to lower the institutional and technological barriers of participation in green procurement. For regions with less developed digital economies, priority should be given to investments in regional carbon emission monitoring platforms, computing centres, and industrial internet infrastructure to strengthen the foundations for carbon data aggregation and intelligent control and to resolve regional bottlenecks in the digital empowerment of green procurement. For state-owned enterprises and high-tech industries, emphasis should be placed on stronger supervision of carbon disclosure and sanctions for greenwashing, to guide their exemplary role and propel low-carbon upgrading throughout the value chain, ultimately enabling equitable and broad-based policy efficacy.

6.3. Limitations and Future Research

This study has certain limitations that future research may address from the following perspectives.

(1) Deepening of the research sample and variables. This study uses data from 2020 to 2024. The short period makes it hard to capture the long-term dynamic carbon reduction effects of green public procurement. Since the sample only covers listed firms, the findings cannot be directly generalised to unlisted enterprises. Key indicators such as AI adoption, carbon disclosure and green procurement participation are developed from corporate annual, ESG and social responsibility reports using keyword frequency and semantic matching. Selective disclosure, inconsistent standards and missing data may lead to measurement errors and biased regression results. Text analysis also cannot fully identify greenwashing content, which affects indicator accuracy. Future research may adopt corporate surveys, questionnaires and third-party carbon verification data to cross-validate and optimise text-based indicators.

(2) Further exploration of influence mechanisms. This study identifies only two major mediating pathways, namely digital empowerment and financial support, while neglecting micro-mechanisms such as organisational cognition, managers' green attention, and supply-chain joint emission reduction. In addition, this paper regards green public procurement as a standalone policy, without exploring its coordination with environmental regulations like carbon emission trading and carbon tax. In fact, the two policies can interact mutually. Good performance in green procurement can support priority allocation or partial exemption of carbon quotas, while compliance with carbon quota rules can also serve as a criterion for green procurement qualification. Moreover, this study fails to fully distinguish greenwashing behaviour and endogeneity bias, which limits causal inference of the net policy effect. Future research

can explore firms' internal governance, examine the joint incentives between green public procurement, carbon quota allocation and carbon tax relief, and evaluate the combined emission reduction effects of mixed policies.

(3) Expanding research contexts and interaction effects. This empirical research is conducted solely on Chinese A-share listed firms, so the conclusions cannot be directly applied to small and medium-sized enterprises or high-emission industries. It also lacks regional and cross-country comparisons, leading to limited external validity. The heterogeneity analysis only covers ownership, industry and region, without discussing contingent factors such as market competition, media supervision and local governance. Future studies can carry out research on supply chains, regional and cross-country comparisons. Researchers may compare green public procurement systems and AI carbon management models across countries to explore policy effects under different institutional backgrounds. It is also worthwhile to analyse how green public procurement promotes joint emission reduction along industrial chains.

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