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-RESEARCH ARTICLE-

DIGITAL ECONOMY AND INDUSTRIAL GREEN TOTAL FACTOR PRODUCTIVITY: EVIDENCE FROM CHINA

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─Abstract─

Digital economy (DE) has emerged as a central catalyst for regional technological advancement, a renewed engine of economic expansion, and an essential pathway for achieving sustainable and low-carbon growth. This study develops a DE index using the CRITIC–TOPSIS approach based on panel data from 30 Chinese provinces spanning 2006–2023 and applies the Super-SBM model to measure industrial green total factor productivity (IGTFP). It systematically investigates both the underlying mechanisms and the spatial heterogeneity of the influence exerted by DE on IGTFP. The empirical findings indicate that DE exerts a strong and statistically significant positive effect on IGTFP, with the most substantial contributions arising from digital

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industrialisation and platform-based activities. In contrast, digital innovation activities do not exhibit a discernible impact on improvements in green productivity. Further mechanism analysis demonstrates that DE promotes IGTFP primarily by facilitating industrial restructuring and accelerating green technological innovation. This effect is further amplified under stricter environmental regulation, as higher regulatory intensity is associated with greater gains in green productivity. Spatial analysis reveals pronounced regional disparities. Eastern and north-eastern provinces benefit most from digitalisation, whereas central and western regions experience constrained outcomes due to deficiencies in infrastructure and innovative capacity. Based on these results, the study concludes that strengthening digital platforms, advancing green technological innovation, and implementing stringent regulatory frameworks supported by effective governance can substantially enhance green productivity performance. Additionally, it advocates the formulation of region-specific policy measures to narrow developmental gaps and achieve more widespread improvements in IGTFP across China.

Keywords: Digital Economy, Industrial Green Total Factor Productivity, Environmental Regulation, Regional Heterogeneity.

INTRODUCTION

The industrial sector remains a cornerstone of China's economy, accounting for more than 30 per cent of gross domestic product and providing employment for a substantial share of the labour force. Historically, however, industrial development has relied on an extensive growth pattern characterised by high inputs, elevated emissions, and intensive consumption of natural resources, thereby exerting considerable pressure on the ecological environment. In light of China's commitment to achieving peak carbon emissions by 2030 and carbon neutrality by 2060 (Zhou & Hu, 2021), the industrial sector faces an urgent need to abandon its factor-driven growth trajectory and transition towards a green, low-carbon, and resource-efficient development model.

IGTFP serves as a core indicator of this transformation, as it not only captures the efficiency of traditional production factors such as labour and capital, but also incorporates undesirable outputs, thereby reflecting both economic performance and environmental outcomes (Jorgenson & Stiroh, 2000; Li & Xu, 2009). Nonetheless, further improvements in IGTFP through conventional technological upgrades or energy structure adjustments are increasingly constrained by high costs, technological bottlenecks, and diminishing marginal returns. Consequently, both academic research and policy formulation require the identification of alternative drivers of green growth, among which the rapid expansion of DE represents a potentially critical breakthrough.

In recent years, DE has emerged as a transformative force reshaping production modes, industrial organisation, and patterns of economic development worldwide. Advances in information and communication technologies, together with the application of big data

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analytics, artificial intelligence, and cloud computing, have demonstrated substantial potential in enhancing productivity, facilitating industrial upgrading, and supporting green transformation (Bukht & Heeks, 2017). In the Chinese context, this trend aligns closely with the strategic shift from high-speed growth towards high-quality development, as emphasised in national policy frameworks such as the New Development Philosophy and the 14th Five-Year Plan. Within this policy environment, digital transformation is increasingly recognised as a pivotal pathway for promoting sustainable and low-carbon industrial development.

Existing academic studies examining the relationship between DE and IGTFP in the industrial sector have largely concentrated on three dimensions, namely overall effects, transmission mechanisms, and non-linear characteristics. First, empirical evidence generally suggests that DE contributes positively to IGTFP, although the magnitude of this effect varies considerably across regions (Wang, Zheng & Yang, 2024). Second, research indicates that DE influences IGTFP through multiple channels, including technological innovation, optimisation of resource allocation, and industrial restructuring (Tang & Lan, 2025). Third, the relationship between DE and IGTFP is often characterised by non-linear and threshold effects, implying that the green productivity gains from digitalisation may depend on specific conditions such as the stringency of environmental regulation or the level of innovation capacity (Liu et al., 2024).

Despite the growing body of literature, research on the linkage between DE development and IGTFP remains fragmented and lacks an integrated analytical framework. Much of the existing work focuses on the contribution of digitalisation to macroeconomic growth or conventional productivity improvements (Feng et al., 2022), while providing limited empirical evidence on the specific mechanisms through which DE enhances IGTFP. In particular, the roles of industrial restructuring and green technological innovation have not been examined in a systematic and unified manner. Although some studies address the application of digital technologies in cleaner production processes and energy efficiency improvements, the moderating influence of environmental regulation is seldom incorporated into empirical models. This omission has contributed to inconsistencies in understanding the joint evolution of digitalisation and IGTFP. Given China’s pronounced regional heterogeneity in terms of development stages, industrial composition, innovation capacity, and resource endowments, neglecting the moderating role of environmental regulation further limits the explanatory power of existing analyses. As a result, comprehensive evidence on how digitalisation drives green transformation under diverse regional conditions remains insufficient (Liu et al., 2025). Additional empirical investigation into the DE–IGTFP relationship is therefore necessary to clarify its operational mechanisms and to inform the design of more differentiated and regionally targeted policy interventions.

Against this background, the present study conducts a systematic examination of the relationship between DE development and IGTFP, with particular emphasis on transmission mechanisms, the moderating role of environmental regulation, and spatial heterogeneity. The contributions of this study are threefold. First, it extends the existing literature by explicitly incorporating environmental performance into the assessment of productivity. Second, it empirically investigates the channels through which DE influences IGTFP by focusing on industrial restructuring and green technological innovation. Third, it integrates environmental regulation into the analytical framework to evaluate its moderating effects, providing evidence of heterogeneous impacts across eastern, north-eastern, central, and western provinces.

LITERATURE REVIEW AND RESEARCH HYPOTHESIS

Literature Review

The concept of DE remains contested, as no universally accepted definition has been established across academic and institutional contexts. Existing interpretations differ according to their emphasis on technological foundations, production factors, or structural characteristics. The term was initially popularised by Araya & Marber (2023), who described it as an economic system underpinned by digital technologies that enable networking and the sharing of human knowledge. Subsequently, Bukht and Heeks (2017) offered a broader interpretation, defining DE as encompassing all economic activities in which digital knowledge and information constitute the primary inputs, supported by modern information networks and driven by productivity improvements and structural optimisation associated with information and communication technologies.

At present, three principal methodological approaches are employed to quantify DE. The value-added approach estimates its direct contribution by calculating the output generated by information and communication technology industries and related services (Barefoot et al., 2018). The composite index approach constructs multidimensional indicators based on variables such as internet penetration, investment in digital infrastructure, and the scale of e-commerce transactions (Bruno et al., 2023). The satellite account approach extends the conventional national accounting framework by incorporating a dedicated digital economy account, thereby providing a more comprehensive representation of its economic significance (Bukht & Heeks, 2017). Each of these approaches exhibits distinct advantages and limitations with respect to data availability, coverage, and international comparability.

Traditional total factor productivity focuses exclusively on labour and capital inputs, while neglecting environmental constraints and undesirable outputs, and therefore provides an incomplete assessment of sustainability performance (Hailu & Veeman, 2000). Green total factor productivity extends this framework by explicitly incorporating energy consumption and pollutant emissions, enabling the joint evaluation of economic efficiency and environmental outcomes (Li & Xu, 2009). In the industrial context, IGTFP reflects the capacity to maximise desirable output while minimising emissions under given constraints on labour, capital, and energy inputs. Measurement techniques can be broadly categorised into parametric approaches, such as stochastic frontier analysis, and non-parametric approaches, such as data envelopment analysis. More advanced models, including slack-based directional distance functions, allow for the simultaneous treatment of desirable and undesirable outputs (Tone, 2001).

Research exploring the influence of DE on IGTFP is relatively recent and remains fragmented. A key debate concerns whether digitalisation can improve efficiency without exacerbating environmental pressures. Empirical evidence generally supports the view that digital technologies promote resource optimisation, reduce inefficiencies, and stimulate green innovation. At the same time, studies also identify diminishing marginal returns, threshold effects, and pronounced regional heterogeneity in these impacts (Li et al., 2020; Feng et al., 2022). At the industrial level, DE is found to enhance IGTFP by lowering production and transaction costs, accelerating technological progress, strengthening market governance, facilitating structural upgrading, and improving human capital accumulation (Qiao et al., 2024). However, these positive effects are conditional upon factors such as the maturity of digital infrastructure, institutional quality, regulatory intensity, and industrial scale, and may even reverse under certain threshold conditions (Zhou & Hu, 2021).

Within the Chinese industrial setting, three primary transmission channels can be identified. First, digital platforms and BDA reduce information asymmetry and transaction costs, thereby improving interregional flows of capital, labour, and technology, correcting resource misallocation, and enhancing green productivity. Second, digitalisation supports green research and development by expanding data availability, accelerating knowledge diffusion, and enabling collaborative innovation platforms, which jointly improve output efficiency while reducing emissions. Third, it facilitates the transition from resource-intensive production towards technology- and knowledge-intensive models, increasing value added and energy efficiency while alleviating environmental pressure at the source. Based on this analytical framework, the following hypothesis is proposed.

H1: *The development of the DE can significantly enhance China's IGTFP.*

Influence Mechanism Hypothesis

Industrial Structure Optimisation

The rapid expansion of DE is profoundly reconfiguring China’s industrial structure, driving a broad-based transformation characterised by the emergence and upgrading of knowledge-intensive sectors, including advanced manufacturing and information technology services. Compared with traditional industries that are heavily dependent on

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energy and material inputs, these emerging sectors typically exhibit higher resource-use efficiency and lower emission intensity. Through this structural shift, DE accelerates the transition of industrial systems towards environmentally sustainable development and, in doing so, promotes improvements in IGTFP via multiple pathways.

First, the widespread adoption of digital business models, such as e-commerce platforms and online service provision, reduces firms' dependence on physical infrastructure and energy-intensive operations. Supported by intelligent algorithms that optimise logistics networks, improve route planning, and strengthen coordinated resource allocation, transport-related emissions per unit of output can be substantially reduced (Shahbaz et al., 2022). Second, advanced digital technologies, including artificial intelligence and the Internet of Things, are increasingly embedded within industrial production processes. These technologies enable precise production scheduling, continuous monitoring of energy consumption, and real-time adjustment of operational parameters, thereby significantly lowering the use of energy and raw materials (Zhiyong et al., 2024). As a result, resource productivity is enhanced, while traditional manufacturing industries undergo ecological upgrading. Based on the above analysis, the following hypothesis is proposed.

H2: *The DE enhances IGTFP by promoting industrial structure optimisation.*

Green Technological Innovation

The sustained deepening of DE has markedly strengthened the supply capacity of green technologies by reshaping prevailing innovation paradigms, thereby emerging as a critical driver of improvements in IGTFP. First, cloud computing and BDA have enabled high-dimensional analysis of environmental data, offering accurate simulation and parameter optimisation support for clean production processes, energy system optimisation, and the research and development of new energy materials. For instance, real-time processing of environmental monitoring data through Internet of Things applications allows enterprises to design pollution control technologies with adaptive response mechanisms and closed-loop resource recovery systems (Wen et al., 2025).

Second, digital platforms lower technology matching costs and mitigate information asymmetry, which accelerates the diffusion and application of green patent technologies across multiple segments of the industrial value chain. A representative example is the large-scale deployment of carbon capture technologies in the steel industry, where extensive diffusion has generated notable network effects (Dogan et al., 2025). Finally, open-source hardware platforms and collaborative cloud-based research and development environments reduce institutional barriers between industry, academia, and research organisations. This integration encourages innovation actors to jointly address shared technological bottlenecks in green development, thereby substantially enhancing the overall efficiency of the green innovation system (Xin et al., 2023). Overall, DE promotes industrial green technological innovation at the systemic level by lowering experimentation costs, compressing research and development cycles, and broadening the scope of application scenarios. On this basis, the following hypothesis is proposed.

H3: *The development of the DE accelerates green technology innovation, thereby improving IGTFP.*

Environmental Regulation

Environmental regulation encompasses the institutional frameworks and policy instruments implemented by governments to achieve environmental protection and sustainable development objectives, including emission constraints, resource governance, information disclosure requirements, and market-oriented incentive mechanisms. Within the context of DE, environmental regulation not only imposes external constraints on corporate pollution behaviour, but also increasingly functions as a catalyst for green technological upgrading and industrial transformation (Lena et al., 2022). On the one hand, compulsory regulatory standards and market-based instruments encourage firms to accelerate their transition towards greener production modes. Mechanisms such as carbon emissions trading and pollutant discharge permit trading incentivise enterprises to adopt digital solutions, including smart metering systems, energy consumption tracking, and emissions monitoring technologies. These tools support more efficient production scheduling and energy management, thereby lowering compliance costs while improving resource-use efficiency (Tian & Feng, 2022).

On the other hand, heightened regulatory pressure prompts firms to expand investment in digital technologies and to strengthen green governance capabilities, particularly in relation to data acquisition, monitoring and feedback systems, and environmental risk management. Enhanced environmental information disclosure further reinforces corporate accountability and transparency under public scrutiny, enabling firms to secure sustainable competitive advantages over the long term (Lee & Lee, 2022). Based on this reasoning, the study argues that environmental regulation not only directly improves firms' environmental performance but also amplifies the positive impact of DE on IGTFP by fostering deeper adoption and integration of digital technologies throughout industrial processes. Accordingly, the following hypothesis is proposed.

H4: *Environmental regulations strengthen the promotional effect of the DE on China's IGTFP.*

Regional Heterogeneity

China exhibits pronounced regional heterogeneity, and these institutional and developmental disparities shape not only the spatial distribution of DE, but also the extent to which it can contribute to improvements in industrial green total factor

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productivity (Sun et al., 2018). Variations in economic foundations, infrastructure endowments, and governance capacity lead to uneven conditions under which digitalisation interacts with industrial green transformation. The eastern coastal region has long occupied a leading position in economic development, supported by a strong industrial base, well-established digital infrastructure, and abundant human capital with high innovation potential. These favourable conditions enable the deep integration and diffusion of digital technologies within industrial production processes, generating synergies between digitalisation and green transformation. As a result, production systems in this region tend to achieve higher energy efficiency, promote cleaner production practices, and reduce pollutant emissions more effectively (Feng et al., 2022).

By contrast, although the central region benefits from relatively advantageous geographical location and transport connectivity, which support manufacturing and processing activities, its overall level of DE development remains substantially lower than that of the eastern region. In many prefecture-level cities and counties, infrastructure related to 5G networks and the industrial internet lags behind, while traditional manufacturing sectors continue to dominate industrial organisation. Under such conditions, firms exhibit limited incentives to pursue green upgrading, and the potential of digital empowerment has not been fully realised.

The western region is characterised by a comparatively weak economic base, complex natural conditions, and underdeveloped digital economic activity. Information infrastructure coverage is both insufficient and uneven, and small and medium-sized enterprises face significant constraints in accessing digital technologies, financing green transformation, and attracting skilled labour (Yang et al., 2023). The north-eastern region, meanwhile, has historically relied on heavy and chemical industries, resulting in rigid industrial structures and slow progress in integrating digital and green transformation pathways (Guo et al., 2020). Although certain provinces possess advantages in equipment manufacturing and intelligent production, overall digital infrastructure remains inadequate, and application scenarios are relatively limited. In addition, population outflows and declining market vitality further weaken the capacity of DE to support green upgrading in this region. In summary, substantial regional disparities in industrial development, digital foundations, innovation capacity, and the pace of green transformation are likely to generate significant imbalances in both the direction and magnitude of the contribution of DE to IGTFP. On this basis, the following hypothesis is proposed.

H5: *The impact of the DE on enhancing IGTFP exhibits significant regional heterogeneity.*

RESEARCH DESIGN

Variable Selection

Explained Variables

In constructing the measurement framework for IGTFP, this study explicitly incorporates the resource and environmental constraints embedded in industrial production and integrates them systematically into the input–output structure. This design allows economic performance and environmental outcomes to be assessed simultaneously within a unified analytical framework. Drawing on Cheng and Kong (2022), Wang and Wang (2023), and related studies, an IGTFP indicator system is established across three core dimensions, namely resource allocation efficiency, the quality of economic growth, and environmental sustainability. The specific configuration of indicators is reported in Table 1.

Table 1: Input-Output Indicator System for IGTFP

Key Indicators	Second-Level Indicators	Variable Description
Input Factors	Capital Input	Net fixed assets of large-scale industrial enterprises adjusted by the fixed asset investment price index (billion yuan)
	Labour Input	Average number of employees in large-scale industrial enterprises (ten thousand people)
	Energy Input	Total energy consumption of large-scale industrial enterprises (in 10,000 tonnes of standard coal)
Expected Output	Economic Output	Industrial added value adjusted by the producer price index (billion yuan)
Non-Expected Output	Environmental Pollution	Industrial wastewater discharge (10,000 tonnes) Industrial sulphur dioxide emissions (10,000 tonnes) Industrial solid waste emissions (10,000 tonnes)

In recent years, the SBM model has emerged to address the limitations of traditional DEA approaches in handling both non-desirable outputs and input redundancies. Unlike radial models, which overlook slack variables and thereby risk information loss, the SBM model effectively integrates non-desirable outputs, including environmental pollutants. When extended within a super-efficiency framework, it allows for the differentiated ranking of efficient decision-making units, substantially improving the precision and comparability of GTFP measurements (Qian et al., 2024). Leveraging these advantages, the present study employs the Super-SBM model incorporating non-desirable outputs to estimate IGTFP. This model is widely recognised for its rigorous theoretical foundation and practical suitability in the evaluation of green total factor productivity (Xu & Li, 2025). Within the Super-SBM framework that accounts for undesirable outputs, the production system is conceptualised as comprising (n) decision-making units, each characterised by three categories of variables: input indicators, desirable output indicators, and undesirable output indicators. The computational formula is expressed as follows:

$$\min \rho^* = \frac{1+\frac{1}{m}\sum_{m=1}^{M} s_m^x / x_{jm}^t}{1-\frac{1}{l+h}\left(\sum_{l=1}^{L} s_l^y / y_{jl}^t + \sum_{h=1}^{H} s_h^b / b_{jh}^t\right)}, \quad s.t. \begin{cases} x_{jm}^t \geq \sum_{j=1, j\neq 0}^{n} \lambda_j^t x_{jm}^t + s_m^x \\ y_{jl}^t \geq \sum_{j=1, j\neq k}^{n} \lambda_j^t y_{jl}^t - s_l^y \\ b_{jh}^t \geq \sum_{j=1, j\neq k}^{n} \lambda_j^t b_{jh}^t + s_h^b \\ \lambda_j^t \geq 0, s_m^x \geq 0, s_l^y \geq 0, j = 1, \cdots, n \end{cases} \tag{1}$$

In this formula, IGTFP—denoted as ρ—represents the efficiency score derived from Eq. (1). The variables x_{jt}, y_{jt}, and b_{jt} refer to the inputs, desirable outputs, and undesirable outputs of the j^{th}DMU at time t. Additionally, s^-, s^+, and s^bcorrespond to the slack (relaxation) vectors associated with inputs, desirable outputs, and undesirable outputs.

Explanatory Variable

Given the systemic and integrated nature of DE, a single metric is insufficient to capture its level of development comprehensively. Consequently, the use of multidimensional and structured composite indicators has become the prevailing approach for assessing DE maturity. Following the framework proposed by Qian, Liu and Pan (2022), this study constructs a comprehensive measurement system comprising four primary dimensions: digital industry development activity (DINDA), digital innovation activity (DINNA), digital user activity (DUSA), and digital platform activity (DPLAA). These dimensions are further operationalised through thirteen detailed indicators, as presented in Table 2.

To quantify DE, this study employs the TOPSIS method combined with CRITIC weighting. The CRITIC approach objectively evaluates the information content and conflict among indicators by analysing both their entropy and correlation, producing a more scientifically justified weighting scheme and mitigating the subjectivity inherent in manual assignment. Subsequently, the TOPSIS technique is applied to perform a holistic assessment across all indicators. By constructing positive and negative ideal solutions, the relative distance of each region's digital development from the ideal benchmark is calculated, yielding a DE index that is both comparative and discriminative (Li et al., 2024; Yin et al., 2024). This methodology not only addresses theoretical disparities and informational independence among the indicators but also enhances the robustness and scientific validity of DE level assessment in practical application.

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Table 2: Evaluation Indicator System for DE Development

Primary Indicators	Second-Level Indicators	Third-Level Indicators
DE	Digital Industry Development Activity (DINDA)	Employment Ratio in the Software, Computer Services, and Information Transmission Sectors
		Software company revenue logarithmic
		Ratio of all society's fixed assets to those in the computer and software industries
	Digital Innovation Activity (DINNA)	Logarithmic value of 5G industry patent authorisations
		Logarithmic value of industrial internet patent authorisations
		Logarithmic value of e-commerce patent authorisations
	Digital User Activity (DUSA)	Mobile phone penetration rate
		Logarithmic value of total telecommunications services
		Number of Internet broadband access users per capita
		Logarithmic value of e-commerce transaction volume
	Digital Platform Activity (DPLAA)	Logarithmic value of the number of domain names
		Logarithmic value of the number of internet users
		Logarithmic value of the number of websites

To maintain comparability across indicators, all raw data are standardised using the deviation standardisation method.

For positive indicators, the standardised value is calculated as follows:

$$y_{ij} = \frac{x_{ij} - \min_i\{x_{ij}\}}{\max_i\{x_{ij}\} - \min_i\{x_{ij}\}} \tag{2}$$

For negative indicators, the standardised value is calculated as follows:

$$y_{ij} = \frac{\max_i\{x_{ij}\} - x_{ij}}{\max_i\{x_{ij}\} - \min_i\{x_{ij}\}} \tag{3}$$

Where, i j represent the province and the indicator, respectively.

Within the CRITIC approach, the contrast strength of the j-th indicator is represented by its standard deviation. The degree of conflict between the j-th and k-th indicators is quantified through their correlation coefficient, while the overall conflict value for the j-th indicator is obtained as follows:

$$C_j = \sigma_j \sum_k \left(1 - \left|r_{kj}\right|\right) \quad j = 1, 2, \cdots, n \tag{4}$$

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Where, the greater the C_j, the more data the j-th indicator contains Eq.(4).

Then, the weight value of the j-th indicator is calculated as Eq.(5):

$$\omega_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{5}$$

The TOPSIS method is used to construct the comprehensive DE index. First, the positive ideal solution S^+ and negative ideal solution S^- are identified from the normalised weighted matrix.

$$\begin{aligned} S^+ &= \left(\max_i y_{i1}, \max_i y_{i2}, \cdots, \max_i y_{in}\right) \\ S^- &= \left(\min_i y_{i1}, \min_i y_{i2}, \cdots, \min_i y_{in}\right) \end{aligned} \tag{6}$$

Next, the Euclidean distances from the i-th province to the positive and negative ideal solutions are calculated as follows:

$$\begin{aligned} D_i^+ &= \sqrt{\sum_{j=1}^{n} \omega_j \left(y_{ij} - y_j^+\right)^2} \\ D_i^- &= \sqrt{\sum_{j=1}^{n} \omega_j \left(y_{ij} - y_j^-\right)^2} \end{aligned} \tag{7}$$

D^+ D^- , which signify the relative positions of the evaluation objects.

In summary, the composite score of the DE of the $i^{\text{-th}}$ province is expressed as:

$$Dig_i^* = \frac{D_i^-}{D_i^- + D_i^+} \quad i = 1, 2, \cdots, m$$

The overall score derived from the TOPSIS method ranges between 0 and 1. A value approaching 1 indicates that the province's DE is nearer to the ideal benchmark, reflecting a higher degree of digitalisation and more advanced development of digital infrastructure, innovation, and platform activities.

Mechanism Variables

Industrial Structure Optimisation

To comprehensively assess the degree of industrial structure optimisation within a region, this study follows the methodology of (Li et al., 2025) and constructs an index encompassing two dimensions: industrial structure advancement (ISA) and industrial structure sophistication (ISS). ISS is measured using a weighted index based on sectoral value added—namely, primary industry value added (V1), secondary industry value added (V2), and tertiary industry value added (V3)—reflecting the vertical progression of the industrial structure along the value chain from low- to high-end activities. Higher values of this index indicate a greater predominance of capital- and knowledge-intensive sectors, signalling a more advanced and sophisticated industrial structure. These two dimensions, although conceptually distinct, operate in a mutually reinforcing manner. The advancement dimension emphasises the rational allocation and balance of industries across the horizontal structure, while the sophistication dimension reflects the vertical progression along the industrial hierarchy, capturing the shift from lower- to higher-value activities. Together, they provide a comprehensive measure of industrial structure optimisation.

Green Technological Innovation

Green technology innovation serves as a critical intermediary between high-quality economic development and the coordinated evolution of the ecological environment, acting as a central driver for both industrial green upgrading and the achievement of dual carbon targets. Patent counts, as a core measure of technological output, reflect not only the level of technological development within a region or enterprise but also the potential for knowledge spillovers (Schiederig et al., 2012). Among these, green technology patents, given their explicit environmental orientation, provide the most direct and effective indicator of green innovation activities.

To quantify the level of green technological innovation, this study adopts two complementary dimensions: green patent applications (GPA) and green patent grants (GPG). Both indicators are standardised by adding 1 to the raw value and applying the natural logarithm, thereby mitigating the impact of extreme values and smoothing scale differences. GPA represents the breadth and intensity of green R&D efforts, reflecting the input side of innovation through early-stage experimentation, knowledge accumulation, and technological exploration. In contrast, GPG captures the output dimension, indicating the maturity, applicability, and commercial potential of green technological outcomes. By incorporating both GPA and GPG simultaneously, this framework captures the dynamic process of green technology innovation—from exploratory development to successful implementation—providing a robust quantitative foundation and more explanatory empirical evidence for analysing its

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contribution to enhancing IGTFP.

Environmental Regulations

To measure the intensity of environmental regulation implemented by local governments in a rigorous and comprehensive manner, this study follows the methodology of Currie and Walker (2019) and constructs an environmental regulation index based on textual analysis of provincial government work reports. These reports, produced annually, function as policy blueprints that outline governance priorities, strategic objectives, and resource allocation plans. The textual content of these documents reflects both the prominence and urgency of environmental governance on the policy agenda. Consequently, the frequency of environment-related keywords serves not only as an effective proxy for regulatory intensity but also captures its temporal variation over time. In practice, environmental keywords were extracted from the government work reports of 30 provincial-level administrations spanning the period 2006 to 2023 (Table 3). The annual occurrence counts of these keywords were then calculated and employed as a quantitative measure of the intensity of environmental regulation at the provincial level.

Table 3: Keywords Related to Environmental Regulation

Environmental Protection	Pollution Discharge	Chemical Oxygen Demand
Environmental Protection	Ecology	Sulphur Dioxide
Pollution	Green	Carbon Dioxide
Energy Consumption	Low Carbon	PM10
Emission Reduction	Air	PM2.5

Compared with conventional approaches that rely on measures such as pollution control investments, pollutant discharge fees, or single economic–physical indicators like emission concentrations, the text-based frequency indicators developed in this study help to mitigate endogeneity concerns. Firstly, provincial government work reports are generally published at the beginning of each year, preceding the economic activities of that period, which reduces the risk of reverse causality. Secondly, policy orientations and signals issued at the provincial level are unlikely to be directly influenced by economic behaviour at the municipal level, thereby enhancing the exogeneity of the measure and supporting its validity as an instrumental variable for empirical analysis.

Control Variables

To enhance the accuracy and interpretability of the model estimations, this study incorporates a set of control variables that account for factors potentially influencing IGTFP.

- Capital Intensity (CI) is calculated as the ratio of net fixed assets of large-scale industrial enterprises to their average number of employees. It captures per capita capital investment, where higher values generally indicate greater resource utilisation capacity and more advanced technological equipment. However, excessive reliance on capital may reduce flexibility in adopting green technologies and hinder adaptability.

- Ownership Structure (OS) is defined as the proportion of total assets held by state-owned industrial enterprises relative to the total assets of all large-scale industrial enterprises, representing the relative influence of the state-owned sector within the regional economy.
- Industrial Agglomeration Degree (IAD) is measured by the share of industrial employment within a province relative to its administrative area, reflecting the spatial concentration of industrial activities.
- Research and Development Intensity (RDI) is expressed as the ratio of internal R&D expenditure to regional GDP, serving as a key indicator of investment in technological innovation.
- Enterprise Scale (ES) is captured by the ratio of total industrial output to the number of medium- and large-scale industrial enterprises, representing the average operational scale of enterprises in the region.
- Environmental Governance Intensity (EGI) is calculated as the ratio of investment in industrial pollution control to industrial added value, indicating the level of financial commitment to pollution management and ecological protection.

Data Sources and Analysis

Data for this study were drawn from a provincial panel covering 30 Chinese provinces from 2006 to 2023, excluding Taiwan, Hong Kong, Macao, and Tibet. The panel was compiled using information from multiple authoritative statistical yearbooks and specialised databases. Primary sources included annual statistical yearbooks published by provincial and municipal governments, as well as official releases from the National Bureau of Statistics, such as the China Statistical Yearbook, China Industrial Statistics Yearbook, China Energy Statistics Yearbook, and Tertiary Industry Statistics Yearbook. To ensure comprehensive indicator coverage and data completeness, supplementary information was obtained from recognised research platforms, including the CSMAR database and the Digital Economy Industry Specialised Database of the Qiyan Academic Big Data Platform. This combination of sources ensures strong consistency, continuity, and reliability of the dataset. During preprocessing, missing values for certain provinces and years were addressed through multiple imputation techniques, mitigating estimation bias from incomplete data and enhancing the statistical robustness of subsequent analyses (Chong et al., 2024).

Descriptive statistics reported in Table 4 indicate that the mean IGTFP is 0.729 (SD = 0.285), suggesting that regional green total factor productivity in China is moderately high but exhibits substantial cross-provincial variation. For the digital economy indicators, the average composite score is 0.464 (SD = 0.155), reflecting a moderate

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overall level of digital development nationwide. Among the four sub-dimensions, digital platform activity demonstrates the strongest performance, implying a relatively mature platform-based industrial environment, followed by digital user activity, which indicates steady improvements in residents' digital adoption. In contrast, digital industry activity (mean = 0.394) and digital innovation activity (mean = 0.368) remain lower, signalling that these areas are still in early or accelerating stages of development.

An examination of skewness and kurtosis shows that most variables do not exhibit severe asymmetry. For example, IGTFP and the composite digital economy score (Dig) have skewness values near zero, indicating approximately symmetrical distributions. DUSA, DINNA, and DPLAA also display small skewness values, broadly consistent with normality assumptions.

Table 4: Descriptive Statistical Analysis of Variables

Variable	N	Mean	SD	Min	Max	p50	Skewness	Kurtosis
IGTFP	540	0.729	0.285	0.296	1.239	0.628	0.133	1.377
Dig	540	0.464	0.155	0.045	0.861	0.465	0.057	2.444
DINDA	540	0.394	0.065	0.116	0.823	0.389	0.988	11.15
DINNA	540	0.368	0.204	0.084	1.000	0.339	0.558	2.646
DUSA	540	0.493	0.132	0.172	0.818	0.482	0.109	2.053
DPLAA	540	0.644	0.164	0.170	0.974	0.663	-0.422	2.605
ISA	540	0.927	0.316	0.176	1.897	0.893	0.294	3.400
ISS	540	10.490	1.028	7.241	12.740	10.560	-0.442	3.093
GPA	540	7.512	1.619	2.485	10.940	7.634	-0.366	2.876
GPG	540	7.009	1.684	1.609	10.730	7.131	-0.374	2.905
lnER	540	3.808	0.826	0.000	4.828	3.951	-3.452	16.250
CI	540	65.53	58.100	10.060	430.400	45.370	2.481	11.020
OS	540	0.493	0.172	0.134	0.836	0.488	-0.217	2.209
IAD	540	0.025	0.036	0.000	0.217	0.015	3.827	19.250
RDI	540	0.016	0.011	0.002	0.072	0.013	2.034	8.278
ES	540	0.805	0.384	0.162	2.718	0.753	1.079	5.207
EGI	540	0.004	0.004	0.000	0.031	0.003	2.733	14.960

However, DINDA exhibits a skewness of 0.988 and a kurtosis of 11.15, reflecting marked right-skewness and high peakedness. This suggests a concentration of high-performing provinces, where a few regions significantly outperform the majority in terms of digital industrial development.

Model Specification

To examine the impact of the DE on IGTFP and test the hypotheses formulated in the theoretical framework, the following basic panel regression model was constructed for empirical estimation of the digital economy's effect on IGTFP:

$$IGTFP_{it} = a_0 + a_1 Dig_{it} + \sum_{j=1}^{K} \varphi_j Control_{it}^{j} + \eta_i + \mu_t + \varepsilon_{it} \tag{9}$$

Where *i* represents provinces; *t* represents periods; the dependent variable IGTFP represents IGTFP; the core explanatory variable *Dig* represents regional digital development level; *η, μ* represents province and time fixed effects; *ε* is the random error term.

Building on the findings of Hünermund and Bareinboim (2025), traditional mediation models are susceptible to endogeneity when applied to panel data, which can result in biased estimates. To address this issue, this study avoids the conventional stepwise regression approach and instead incorporates the mediator variable within a fixed effects framework. This approach, combined with controls for potential confounding factors, enhances the reliability and robustness of the estimated mediation effects.

$$Mediator_{it} = \beta_0 + \beta_1 Dig_{it} + \sum \varphi_j control_{it}^{j} + \eta_i + \mu_t + \varepsilon_{it} \tag{10}$$

Where *Mediator* is the mediating variable. If β_1 is positive, it indicates that the DE can directly exert a positive impact on the mechanism variable.

To investigate the moderating role of environmental regulations, this study develops the following moderation effect model to assess whether the influence of the DE on IGTFP varies significantly with differing levels of regulatory intensity.

$$IGTFP_{it} = \chi_0 + \chi_1 Dig_{it} + \chi_2 ER_{it} + \chi_3 Dig_{it} \times ER_{it} + \sum_{j=1}^{K} \varphi_j Control_{it}^{j} + \eta_i + \mu_t + \varepsilon_{it} \tag{11}$$

The intensity of environmental control in area i during time t is denoted by ERit in Eq. (11). The term "Digit ×ERit" refers to the way in which environmental regulation interacts with DE. The significance of the interaction coefficient is examined to determine whether environmental regulation meaningfully moderates the influence of the digital economy in promoting industrial green transformation.

EMPIRICAL RESULTS AND ANALYSIS

Analysis of Baseline Regression Results

Table 5 presents the regression results, revealing a substantial and multifaceted impact of the DE on IGTFP. Provinces exhibiting higher levels of digital development tend to achieve superior IGTFP, as evidenced by the significant coefficient of the composite DE index in column (1), which is 0.826 at the 5% significance level.

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Table 5: Baseline Regression Results

VARIABLES	(1)	(2)	(3)	(4)	(5)
	IGTFP	IGTFP	IGTFP	IGTFP	IGTFP
Dig	0.826**				
	(0.382)				
DINDA		0.583*			
		(0.329)			
DINNA			-0.036		
			(0.162)		
DUSA				0.578**	
				(0.294)	
DPLAA					0.818**
					(0.325)
CI	-0.001*	-0.001*	-0.001*	-0.001**	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OS	0.066	0.050	0.008	0.018	0.032
	(0.194)	(0.192)	(0.194)	(0.193)	(0.196)
IAD	-1.809*	-2.602**	-2.369**	-1.704	-0.994
	(1.092)	(1.134)	(1.081)	(1.156)	(1.175)
RDI	-0.326	-0.169	1.224	0.631	2.129
	(4.309)	(4.341)	(4.277)	(4.321)	(4.422)
ES	0.483***	0.442***	0.459***	0.482***	0.491***
	(0.057)	(0.056)	(0.057)	(0.057)	(0.056)
EGI	-11.143***	-12.171***	-11.612***	-11.344***	-9.946***
	(3.408)	(3.487)	(3.533)	(3.493)	(3.306)
Constant	0.066	0.280	0.499***	0.182	-0.140
	(0.245)	(0.177)	(0.142)	(0.197)	(0.289)
Observations	540	540	540	540	540
Province	YES	YES	YES	YES	YES
Year fe	YES	YES	YES	YES	YES
R^2	0.743	0.742	0.740	0.742	0.745

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively; standard deviations are shown in parentheses.

This finding indicates that improvements in digital infrastructure, adoption of advanced technologies, and expansion of digital applications contribute to enhanced green productivity by increasing energy efficiency, reducing pollution, and minimising resource waste through more precise process control and optimised supply chain management. At the 10% significance level, digital industry activity shows a coefficient of 0.583 (column 2), while digital user activity exhibits a coefficient of 0.578 at the 5% level (column 4). The particularly strong contribution of platform-based economic models is highlighted in column (5), where digital platform activity demonstrates a considerably larger impact (coefficient = 0.818) on IGTFP.

In contrast, digital innovation activity, reported in column (3) with a coefficient of -0.036, is not statistically significant, suggesting that current innovation initiatives have

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yet to yield measurable improvements in IGTFP. This may reflect a misalignment between certain innovations and green development objectives or delays in the commercialisation of green technologies. The adjusted R^2 exceeds 0.740 across all models, indicating strong statistical robustness and explanatory power after controlling for year and provincial fixed effects, thereby supporting the first hypothesis. Overall, the results demonstrate that the expansion of digital industries and activity on digital platforms exerts a significant and positive influence on IGTFP, highlighting the complementary relationship between digitalisation and green transformation in the industrial sector.

Endogeneity Treatment and Robustness Tests

Endogeneity Treatment Based on the System Generalised Method of Moments

To address potential estimation bias stemming from endogeneity, this study employs a system GMM estimator combined with two-stage least squares, with particular focus on the core explanatory variable, digital economic development (Ullah et al., 2021). Column 1 of Table 6 presents the system GMM results, including the one-period lag of the dependent variable. The lagged term exhibits a coefficient of 0.705, significant at the 1% level, indicating that IGTFP is strongly influenced by its previous values. After accounting for this dynamic persistence, the coefficient of the DE remains positive at 0.332 and is statistically significant at the 10% level. This demonstrates that digital economic development continues to foster improvements in IGTFP even when controlling for endogeneity and dynamic effects, thereby confirming the robustness of the empirical findings and mitigating concerns related to potential endogeneity.

Endogeneity Treatment Based on the Instrumental Variable Approach

This study constructs instrumental variables based on historical infrastructure, specifically using the number of post offices and fixed telephone lines in each province in 1984, along with the lagged number of internet users. Column (2) of Table 6 reports the corresponding two-stage least squares (2SLS) estimates (Xu et al., 2025). These instruments are employed to re-estimate the effect of the digital economy on IGTFP, addressing potential endogeneity concerns. The results support a causal interpretation, indicating that digital economic development continues to exert a positive influence on green total factor productivity. Specifically, the IV-estimated coefficient for DE is 2.681, significant at the 10% level. The Kleibergen-Paap rk LM statistic confirms the validity of the instruments, rejecting the null hypothesis of under-identification at the 5% significance level, which demonstrates a significant correlation between the instruments and the endogenous regressor. Furthermore, the Kleibergen-Paap rk Wald F statistic is 24.045, exceeding the relevant Stock-Yogo critical values, indicating that weak instrument concerns are not present.

Table 6: Results of Endogeneity Treatment

VARIABLES	(1)	(2)
	IGTFP	IGTFP
L.*IGTFP*	0.705***	
	(0.076)	
Dig	0.332*	
	(0.186)	
IV		2.681*
		(1.522)
Observations	510	510
Control variables	YES	YES
Province	YES	YES
Year	YES	YES
R^2	/	0.054
Kleibergen-Paap rk LM statistic		6.530
Kleibergen-Paap rk Wald F statistic		24.045

Robustness Test by Reducing Control Variables

The robustness checks reported in Table 7 indicate that the positive effect of the DE on IGTFP remains consistent, even when the set of control variables is reduced. In column (1), the coefficient for the composite digital economy index (Dig) remains significantly positive, demonstrating that overall digitalisation continues to drive improvements in IGTFP. Disaggregated analyses show that the sub-dimensions DINDA, DUSA, and DPLAA each exhibit significant and positive effects in their respective models, indicating that progress across different aspects of the digital economy reliably promotes IGTFP growth. Although the coefficient for DINNA is not statistically significant, its positive direction aligns with the baseline results, further supporting the robustness and explanatory validity of the core findings.

Table 7: Robustness Test Results: Reducing Control Variables

VARIABLES	(1)	(2)	(3)	(4)	(5)
	IGTFP	IGTFP	IGTFP	IGTFP	IGTFP
Dig	0.822**				
	(0.391)				
DINDA		0.581*			
		(0.331)			
DINNA			-0.026		
			(0.164)		
DUSA				0.581**	
				(0.293)	
DPLAA					0.802**
					(0.321)
CI	-0.001*	-0.001**	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

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OS	0.068	0.051	0.001	0.014	0.017
	(0.192)	(0.190)	(0.192)	(0.192)	(0.193)
IAD	-1.857**	-2.624***	-2.204***	-1.612*	-0.724
	(0.872)	(0.946)	(0.844)	(0.925)	(1.039)
ES	0.482***	0.442***	0.460***	0.483***	0.491***
	(0.057)	(0.056)	(0.057)	(0.057)	(0.056)
EGI	-11.161***	-12.177***	-11.568***	-11.312***	-9.878***
	(3.434)	(3.490)	(3.532)	(3.501)	(3.308)
Constant	0.062	0.278*	0.517***	0.192	-0.089
	(0.231)	(0.162)	(0.121)	(0.189)	(0.261)
Observations	540	540	540	540	540
Province	YES	YES	YES	YES	YES
Year fe	YES	YES	YES	YES	YES
R^2	0.744	0.742	0.740	0.742	0.745

Robustness Test by Excluding the 2020 Sample

Table 8 evaluates the robustness of the DE's impact on IGTFP by re-estimating the models after excluding the 2020 observations, thereby reducing potential distortions from exceptional events such as the COVID-19 pandemic. The results show that the main variable, Dig, as well as its sub-dimensions DINDA, DUSA, and DPLAA, retain significant positive coefficients across all specifications, consistent with the baseline findings and confirming the persistent role of digital development in enhancing IGTFP. The coefficient for DINNA remains statistically insignificant.

Table 8: Robustness Test Results: Excluding the 2020 Sample

VARIABLES	(1) IGTFP	(2) IGTFP	(3) IGTFP	(4) IGTFP	(5) IGTFP
Dig	0.819**				
	(0.404)				
DINDA		0.727**			
		(0.333)			
DINNA			-0.028		
			(0.171)		
DUSA				0.598*	
				(0.317)	
DPLAA					0.653**
					(0.332)
CI	-0.001	-0.001	-0.001	-0.001*	-
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OS	0.048	0.048	-0.007	-0.002	0.008
	(0.203)	(0.200)	(0.203)	(0.202)	(0.204)
IAD	-1.461	-2.274*	-1.995*	-1.291	-0.955
	(1.141)	(1.173)	(1.116)	(1.212)	(1.216)
RDI	-1.014	-1.141	0.573	-0.093	1.231
	(4.419)	(4.458)	(4.399)	(4.432)	(4.548)
ES	0.459***	0.414***	0.436***	0.459***	0.463***

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	(0.060)	(0.059)	(0.061)	(0.061)	(0.060)
EGI	-11.385***	-12.568***	-11.895***	-11.664***	-10.496***
	(3.466)	(3.553)	(3.585)	(3.551)	(3.348)
Constant	0.107	0.258	0.524***	0.210	0.023
	(0.253)	(0.177)	(0.145)	(0.202)	(0.293)
Observations	510	510	510	510	510
Province	YES	YES	YES	YES	YES
Year fe	YES	YES	YES	YES	YES
R^2	0.744	0.744	0.741	0.743	0.744

Robustness Test by Replacing the Dependent and Independent Variables

Table 9 reports additional robustness checks by varying both the dependent variable and the core explanatory measure to assess the consistency of the results. Column (1) presents the benchmark regression, with IGTFP calculated using the Super-SBM model as the dependent variable. In column (2), the dependent variable is replaced with IGTFP estimated via the EBM model, which improves the precision and reliability of efficiency measurement (Yu et al., 2023). Column (3) retains the EBM-based IGTFP but substitutes the DE index with an alternative measure, Dig_pca, derived from principal component analysis rather than the original CRITIC-TOPSIS method, reducing subjectivity in index construction (Pan et al., 2022). Across all specifications, the DE maintains a positive impact on IGTFP. Specifically, the Dig coefficients are 0.826 and 0.454 in columns (1) and (2), respectively, both statistically significant, while the Dig_pca coefficient in column (3) is 0.054, significant at the 1% level. These results confirm that the positive effect of digital economic development on IGTFP is robust to alternative measurement approaches.

Table 9: Robustness Test Results: Replacing the Dependent Variable and Core Explanatory Variables

VARIABLES	(1)	(2)	(3)
	IGTFP	IGTFP_EBM	IGTFP_EBM
Dig	0.826**	0.454**	
	(0.382)	(0.185)	
Dig_pca			0.054***
			(0.018)
CI	-0.001	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)
OS	0.066	0.057	0.053
	(0.194)	(0.108)	(0.105)
IAD	-1.809*	3.305***	2.293***
	(1.092)	(0.606)	(0.677)
RDI	-0.326	-1.585	-1.893
	(4.309)	(2.142)	(2.122)
ES	0.483***	0.274***	0.245***
	(0.057)	(0.024)	(0.024)

EGI	-11.143***	-4.009**	-4.984***
	(3.408)	(1.838)	(1.895)
Constant	0.066	0.251**	0.512***
	(0.245)	(0.120)	(0.065)
Observations	540	540	540
Province	YES	YES	YES
Year fe	YES	YES	YES
R^2	0.743	0.811	0.812

Influence Mechanism Analysis

Transmission Mechanism via Industrial Structure Optimisation

Regarding industrial structure optimisation, Table 10 examines the effect of the DE on ISA and ISS in Columns (1) and (2), respectively. The results indicate that digital development significantly and consistently enhances both dimensions. Specifically, the coefficient of Dig on ISA is 0.991 and on ISS is 2.476, both significant at the 1% level. These findings suggest that the DE promotes industrial upgrading and improves resource allocation efficiency by empowering all components of the industrial chain, facilitating cross-industry factor allocation, and advancing high-tech and emerging sectors. The optimisation of industrial structure serves as a mechanism for improving IGTFP in China. ISA encourages a shift toward technology- and knowledge-intensive sectors, strengthens the interaction between green inputs and efficient outputs, and supports environmentally sustainable economic growth through more efficient resource utilisation. Concurrently, ISS enhances the efficiency of resource allocation across industries, reduces redundancy, limits duplicate construction, and improves the cooperative performance of the industrial system. These processes not only alleviate environmental pressures but also expand the potential for green productivity. Consequently, Research Hypothesis 2 is empirically supported.

Table 10: Results of the Transmission Mechanism Test

VARIABLES	(1)	(2)	(3)	(4)
	ISA	ISS	GPA	GPG
Dig	0.991***	2.476***	3.984***	4.079***
	(0.312)	(0.236)	(0.583)	(0.561)
CI	0.001**	-0.000**	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.001)
OS	-0.457***	-0.305***	0.098	0.434
	(0.136)	(0.113)	(0.288)	(0.284)
IAD	1.241	-0.167	-9.185***	-8.998***
	(1.139)	(0.681)	(1.682)	(1.501)
RDI	1.545	-3.668	32.158***	37.435***
	(3.364)	(2.476)	(6.008)	(5.859)
ES	0.445***	0.115***	0.078	0.028
	(0.041)	(0.032)	(0.070)	(0.073)

EGI	-5.061*	-3.263	-2.082	-9.119
	(2.741)	(2.587)	(5.539)	(6.068)
Constant	0.255	9.500***	4.989***	4.235***
	(0.193)	(0.158)	(0.358)	(0.343)
Observations	540	540	540	540
Province	YES	YES	YES	YES
Year fe	YES	YES	YES	YES
R^2	0.885	0.993	0.983	0.984

Transmission Mechanism Via Green Technological Innovation

Regarding the green technological innovation mechanism, Table 10, Columns (3) and (4) present the effect of the DE on GPA and GPG. The estimated coefficients of Dig are 3.984 and 4.079, respectively, both significant at the 1% level, indicating a strong and positive influence of digital development on green innovation. From a theoretical perspective, green technological innovation constitutes a key driver of IGTFP enhancement. GPA captures the intensity of R&D activities, and an increase in GPA facilitates the sustained generation of green technologies. GPG reflects the maturity and commercialisation of these innovations, signifying the translation of technological advancements into actual production and utilisation, thereby improving resource efficiency, reducing emissions, and optimising energy structures. Together, GPA and GPG form a closed-loop system linking the development and application of green technologies. Consequently, the DE not only expands the quantitative output of green technologies but also promotes their qualitative conversion into industrial applications, establishing a robust foundation for high-quality, green transformation in China's industrial sector. These findings provide empirical support for Research Hypothesis 3.

Role of Environmental Regulation

Table 11, Column (1) examines the moderating role of environmental regulation intensity in the relationship between the DE and China's IGTFP. The interaction term, Dig × lnER, has a coefficient of 0.170, significant at the 5% level, indicating that stronger environmental regulation amplifies the positive effect of the DE on IGTFP. In other words, higher regulatory intensity increases the marginal productivity gains arising from digitalisation.

Table 11: Moderation Effect Results

VARIABLES	(1)	(2)	(3)
	IGTFP	IGTFP	IGTFP_EBM
Dig	0.633*		0.303*
	(0.365)		(0.177)
Dig_pca		0.029	
		(0.034)	
lnER	0.042**	0.046	0.027
	(0.018)	(0.016)	(0.010)

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Dig*lnER	0.170**		0.148***
	(0.085)		(0.046)
Dig_pca *lnER		0.051***	
		(0.019)	
CI	-	-0.001	-0.000
	(0.000)	(0.000)	(0.000)
OS	0.006	-0.070	0.010
	(0.196)	(0.195)	(0.106)
IAD	-2.024*	-3.259***	3.069***
	(1.069)	(1.238)	(0.637)
RDI	-2.077	-1.780	-2.977
	(4.391)	(4.371)	(2.113)
ES	0.482***	0.457***	0.274***
	(0.055)	(0.055)	(0.023)
EGI	-11.038***	-11.309***	-3.886**
	(3.261)	(3.088)	(1.809)
Constant	0.721***	0.723***	0.720***
	(0.007)	(0.006)	(0.004)
Observations	540	540	540
Province	YES	YES	YES
Year fe	YES	YES	YES
R^2	0.746	0.748	0.817

This finding supports a positive feedback mechanism between environmental regulation and the DE, consistent with the weak Porter hypothesis. The underlying rationale is that heightened regulatory pressure increases firms' sensitivity to compliance costs and associated benefits, thereby accelerating digital transformation. By leveraging real-time monitoring, process optimisation, supply chain coordination, and data-driven green management, enterprises can convert external constraints into internal efficiency gains. Simultaneously, the DE improves the measurability, tradability, and financeability of emission reductions, maximising regulatory incentives and creating a virtuous cycle in which environmental regulation and digital development mutually reinforce green productivity.

Robustness, tests in Columns (2) and (3) support the findings. In case Dig is substituted by the principal component-based index Digpca, the term Dig pca Dig pca*lnER has a coefficient of 0.051, which is significant at 1 percent. When the dependent variable is replaced with IGTFP estimated using the EBM model, the coefficient for Dig × lnER is 0.148, significant at the 1% level. These consistent results confirm that environmental regulation strengthens the positive impact of the DE on IGTFP, thereby providing empirical support for Research Hypothesis 4.

Regional Heterogeneity Analysis

The results in Table 12 reveal that the impact of the DE on industrial IGTFP varies markedly across China's regions, reflecting disparities in policy environments,

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technological infrastructure, and industrial structures due to uneven regional development. These findings provide support for Research Hypothesis 5. In the eastern region (Column 1), the DE exhibits the strongest positive effect, with a coefficient of 0.922 significant at the 1% level. This outcome can be attributed to the region's well-established DE infrastructure, advanced information networks, high level of industrial digitalisation, and concentration of green innovation resources. The presence of high-tech enterprises, strong absorptive capacity, and efficient innovation conversion mechanisms enables the eastern region to leverage digital technologies effectively for green production, thereby enhancing energy efficiency and promoting sustainable growth.

In contrast, the central region (Column 2) shows a DE coefficient of -0.159, which is not statistically significant, indicating that digital development has not yet translated into tangible gains in green productivity. Contributing factors include slower digitalisation, reliance on traditional manufacturing, and limited adoption of digital technologies in enterprises. The findings also highlight that industrial agglomeration remains a significant driver of IGTFP in this region, suggesting that productivity improvements are currently more attributable to clustering effects than to digitalisation.

For the western region (Column 3), the DE coefficient is 0.078 and statistically insignificant. Despite recent investments in digital infrastructure and supportive green policies, the region's low economic base, limited digital penetration, and weaker green innovation capabilities have constrained the effective transformation of DE into measurable productivity gains. The significantly negative coefficient for R&D intensity further indicates that the efficiency and conversion of green innovation outputs in this region still require substantial improvement. The north-eastern region (Column 4) demonstrates a significant positive DE effect, with a coefficient of 1.071 at the 5% level. Here, the integration of digital technologies with traditional industries, facilitated by initiatives such as smart manufacturing, green transformation projects, and digital industrial parks, has enhanced resource efficiency and pollution control, effectively converting digital development into improvements in IGTFP.

Table 12: Regional Heterogeneity Results

VARIABLES	(1)	(2)	(3)	(4)
	East	**Central**	**West**	**Northeast**
Dig	0.922***	-0.159	0.078	1.071**
	(0.336)	(0.832)	(0.529)	(0.424)
CI	0.000	-0.003**	-0.000	-0.002*
	(0.001)	(0.002)	(0.000)	(0.001)
OS	-0.064	-0.513	0.225	-0.224
	(0.220)	(0.409)	(0.168)	(0.513)
IAD	1.329	23.072***	6.019	19.976
	(0.812)	(6.487)	(15.279)	(17.136)

RDI	11.326**	-5.450	-13.891***	0.841
	(4.649)	(8.855)	(4.206)	(6.609)
ES	0.319***	0.364***	0.216***	0.377***
	(0.062)	(0.100)	(0.035)	(0.037)
EGI	-2.732	-17.303**	-1.956	0.845
	(4.360)	(8.287)	(2.304)	(4.297)
Constant	-0.284	0.611	0.467	-0.100
	(0.277)	(0.458)	(0.311)	(0.333)
Observations	180	108	198	54
Province	YES	YES	YES	YES
Year	YES	YES	YES	YES
R^2	0.866	0.669	0.775	0.902

CONCLUSION AND POLICY IMPLICATIONS

This study constructs a CRITIC-TOPSIS-based DE index using panel data from 30 Chinese provinces spanning 2006–2023, employing fixed-effects models to assess its mechanisms and regional heterogeneity in promoting IGTFP. The DE index is combined with the Super-SBM model to measure IGTFP. Empirical results indicate that China's digital expansion positively affects IGTFP, supporting high-quality, low-carbon industrialisation across alternative measurement approaches, model specifications, and sample scenarios. Analysis of the DE index components reveals that digital industry development and digital platform activity exert the strongest influence on IGTFP, enhancing resource allocation efficiency, inter-industry information flows, and the alignment of green technologies with industrial demand. Digital tools facilitate cross-regional collaboration and reduce transaction costs, supporting the diffusion and adoption of green innovations. In contrast, digital innovation activity exhibits a smaller, statistically insignificant effect, suggesting that innovation outcomes require more time or better commercialisation pathways to translate into measurable productivity gains. Mechanism analysis identifies two primary pathways through which DE enhances IGTFP: industrial structure upgrading and green technological innovation. Digitalisation drives structural upgrading by shifting economic activity toward knowledge- and technology-intensive service sectors and increasing the vertical sophistication of industries, promoting higher-value, environmentally efficient production. These changes, coupled with greener consumption patterns and digital lifestyles, strengthen both supply- and demand-side green performance. Simultaneously, DE fosters green technological innovation by reducing R&D uncertainty, improving data availability for environmental simulations, optimising production parameters, and accelerating the dissemination and industrial application of green patents. This dual effect enhances both the quantity and quality of green innovations, supporting long-term environmental efficiency.

Environmental regulation amplifies the DE's impact on IGTFP. Higher regulatory intensity increases the marginal productivity gains of digitalisation by incentivising firms to adopt digital monitoring, compliance, and process optimisation. Digital technologies enhance transparency and measurability, converting regulatory pressure into operational efficiency and green competitiveness, consistent with the weak Porter Hypothesis. Regional heterogeneity is pronounced. The eastern and north-eastern regions benefit most from DE due to advanced digital infrastructure, industrial digitalisation, strong innovation environments, and supportive institutions, enabling effective transformation of digital technologies into green productivity. Conversely, the central region shows non-significant effects, constrained by slower digitalisation, traditional manufacturing focus, and limited integration with green objectives. The western region also exhibits weak impacts due to underdeveloped infrastructure, lower innovation capacity, and a less mature industrial base, highlighting the need for region-specific policies.

Policy implications include: strengthening alignment between digital platforms and industrial demand, expanding national computing and data governance infrastructures, and facilitating cross-regional data flows; implementing "regulation-smart empowerment" strategies combining digital monitoring with carbon pricing, green finance, and tax incentives; promoting industrial restructuring and green technological innovation through low-carbon upgrades, AI, big data, and circular-economy technologies; and adopting targeted regional strategies, such as increased investment in digital infrastructure, green manufacturing bonds, and innovation diffusion funds in central and western provinces. Collectively, these measures can accelerate digitalisation and green development, reduce regional disparities, and enhance China's national-level IGTFP growth.

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