To cite this article: Jiarong Huang, Lixin Zhou*, Si Yi. (2026). *Has the Integration of Digital and Real Economies Promoted Green Innovation in the Yangtze River Economic Belt? Journal of Financial and Economic Dynamics*, 1(1), 1-20; https://doi.org/10.66361/jfed.46

Has the Integration of Digital and Real Economies Promoted Green Innovation in the Yangtze River Economic Belt?

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Abstract: Against the backdrop of China's "Dual Carbon" goals and a globally evolving, increasingly sophisticated climate governance framework, clarifying how the integration of the digital and real economies (Digital-real Integration, DRI) drives green innovation (GIP) is critical to advancing sustainable development. Using panel data from 105 prefecture-level cities across the Yangtze River Economic Belt (YREB) over the period 2011–2021, this study applies fixed-effects, mediation, and moderation models to carry out empirical analysis. Our results indicate that DRI exerts a significant positive impact on GIP, largely through the cultivation of new quality productive forces. Moreover, environmental regulation and local government competition further amplify the positive effect of DRI on GIP, while government attention to digital development imposes a significant negative moderating influence. Heterogeneity analysis further shows that the promotional role of DRI is more notable in non-central cities and regions with relatively low entrepreneurial activity. This research confirms that DRI is not only a systemic transformation of the techno-economic paradigm but also a key mechanism to address "green imbalance" and promote coordinated regional transformation. These findings deliver empirical support and policy guidance for green digital development in similar river basins and economic zones around the world.
Keywords: Digital-real integration; Green innovation; New quality productive forces; Environmental regulation; Government competition.

1. Introduction

Over the past four decades, China has made remarkable strides in economic development. However, its long-standing extensive growth model, which is heavily dependent on factor inputs and scale expansion, has simultaneously given rise to enduring challenges, such as high energy consumption, worsening environmental pollution, and rising carbon emissions [1,2]. Against this backdrop, together with the formal proposal of China's "Dual Carbon" goals and the continuous consolidation of the global climate governance regime, promoting green innovation (GIP) has become imperative for achieving sustainable development [3]. GIP not only effectively alleviates environmental pressures through clean technologies and low-carbon processes [4,5] but also fosters the development of emerging industries, which in turn drives the transformation of the economic structure toward green and low-carbon paradigms [6,7]. As such, exploring a new development model that can deeply integrate modern technologies with the production system to provide systematic support for GIP is of particular urgency [8].

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Digital-Real Integration (DRI), which refers to the integration of the digital and real economies, is driving systemic transformations in production factors, productivity, and production relations [9] and thereby creating new pathways for GIP. Specifically, the deep permeation of digital technologies into the real economy [10] significantly enhances production efficiency [11,12], reduces business operational costs [13], and optimizes industrial structure [8]. This process in turn releases additional resources that can be directed towards GIP initiatives. According to data from the China Academy of Information and Communications Technology, the scale of China's digital economy reached 56.2 trillion yuan in 2024, accounting for 43.5% of GDP. Within this, the scale of industrial digitalization amounted to 46.1 trillion yuan, representing a year-on-year increase of 7.1%. The penetration rates of the digital economy into the agricultural, industrial, and service sectors have reached 11.2%, 26.3%, and 47.1%, respectively. This rapidly deepening integration process is increasingly becoming a vital driving force for GIP [9,14].

Existing studies have examined the links between the digital economy and environmental performance [15], sustainable development [11], green growth [7], and pollution and carbon reduction [16,17]. However, much of this literature still adopts a single "digital economy" perspective and pays limited attention to digital–real integration (DRI) as a process where digital technologies are embedded into the real economy and co-evolve with industrial systems. The relatively small body of DRI-oriented research tends to focus on the national or firm level, leaving a lack of systematic evidence at the river-basin economic system scale regarding whether and how DRI promotes green innovation (GIP) through identifiable transmission channels, as well as the institutional and governance contexts under which such effects vary. In particular, prior studies provide insufficient and inconsistent evidence on the mechanism pathways through which DRI affects green innovation. For example, they rarely clarify how DRI fosters new quality productive forces to enhance GIP and how contextual factors such as environmental regulation, local government competition, and government digital attention shape the boundary conditions of this relationship.

To address these gaps, this study takes the Yangtze River Economic Belt (YREB) as its empirical setting. Spanning 11 provinces and municipalities across eastern, central, and western China, the YREB accounted for 47.3% of the nation's GDP in 2024. It serves not only as China's most vital engine of economic growth [7] but also as a strategic ecological shield. The region exhibits pronounced spatial gradients: eastern cities are advanced in digital infrastructure and innovation capacity, while central and western areas face constraints in technology adoption and institutional support. Combined with the national policy directive of "prioritizing ecological conservation and prohibiting excessive development," the YREB offers an ideal quasi-natural experimental setting to investigate how DRI shapes GIP across diverse institutional and developmental contexts [18].

This study contributes in three main dimensions. First, theoretically, it moves beyond treating the digital economy merely as an external enabling tool by conceptualizing DRI as a co-embedded and restructuring process between digital technologies and real industries, and by elucidating the intrinsic mechanism through which DRI enhances GIP primarily via fostering new quality productive forces. By incorporating moderation analyses of environmental regulation, local government competition, and government digital attention, the study further clarifies the boundary role of institutional and governance contexts, enriching the theoretical understanding of green transition. Second, empirically, while existing work has largely concentrated on national- or firm-level evidence, this paper provides river-basin-scale evidence using a panel of 105 prefecture-level cities in the YREB. Third, from a policy and practical perspective, the findings indicate that DRI exerts a stronger promotional effect on GIP in non-central cities and regions with lower entrepreneurial activity, which highlights DRI's distinctive value in addressing "green imbalance" and fostering coordinated regional transformation. The results offer empirical support for the YREB's strategic principle of "prioritizing ecological protection and pursuing green development," and provide policy-relevant insights for other river basins and economic zones seeking synergistic digital and green transformation.

2. Literature Review

2.1 Digital-real integration (DRI)

Over the past four decades, China has made remarkable strides in economic development. However, its long-standing extensive growth model, which is heavily dependent on factor inputs and scale expansion, has simultaneously given rise to enduring challenges, such as high energy consumption, worsening environmental pollution, and rising carbon emissions [1,2]. Against this backdrop, together with the formal proposal of China's "Dual Carbon" goals and the continuous consolidation of the global climate governance regime, promoting green innovation (GIP) has become imperative for achieving sustainable development [3]. GIP not only effectively alleviates environmental pressures through clean technologies and low-carbon processes [4,5] but also fosters the development of emerging industries, which in turn drives the transformation of the economic structure toward green and low-carbon paradigms [6,7]. As such, exploring a new development model that can deeply integrate modern technologies with the production system to provide systematic support for GIP is of particular urgency [8].

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economic zones seeking synergistic digital and green transformation.
The DRI has attracted growing attention from both academic and policy circles as a vital pathway for driving high-quality economic development [9]. Existing research has primarily evolved along three dimensions: conceptual clarification, identification of economic effects, and methodological evolution in measurement.
In terms of conceptual foundations, DRI is rooted in the theory of industrial convergence. Yoffie (1996) originally defined industrial convergence as a process through which digital technologies enable functional integration across products and services [19]. Curran et al. (2010) later expanded this notion and emphasized that convergence encompasses not only technological integration but also transformations in market structures, business models, and regulatory frameworks [20]. As the literature evolved, scholars began examining sector-specific manifestations of DRI. Hojeghan and Esfangareh (2011) investigated the integration of digital technologies into tourism [21], while Cheng and Zhou (2023) explored digital transformation pathways in agriculture. These studies collectively illuminate the contextual and sectoral nuances of DRI in practice [22]. More recently, a systemic perspective has gained traction. Sun et al. (2024a) characterized DRI as a dynamic, reciprocal interaction between the digital and real economies that fosters a virtuous cycle of co-evolution [5]. Meng (2023) further argued that DRI involves a systemic reconfiguration of traditional industrial systems through the infusion of data as a key production factor, digital technologies, and platform-based organizational models, which in turn enables comprehensive innovation and efficiency gains [8]. Building on this evolving understanding, this study conceptualizes DRI not merely as the adoption of digital tools but as a structural transformation driven by data and digital technologies, where digital industrialization and industrial digitization reinforce each other to reshape productivity, resource allocation, and innovation capacity across the economy.
Regarding its impacts, evidence has been documented across different levels of analysis. At the macro level, Hong and Ren (2023) found that DRI fosters the transformation and upgrading of the real economy through the embedding of data factors and the development of the platform economy [23]. Xin et al. (2023) demonstrated its strategic value for regional energy transitions [24], while Liu et al. (2024), using a national sample, confirmed its role in enhancing green development efficiency [9]. At the meso level, focusing on the industrial sector, Meng (2023) revealed its driving mechanisms for industrial green transformation [8]. At the micro level, Sun et al. (2024a) identified that DRI promotes industrial synergy through optimized information allocation, but they also noted potential new risks such as exacerbating capital market volatility [5].
In terms of measurement, prevailing methodologies primarily include patent analysis, input-output analysis, and the coupling coordination degree model. Patent analysis focuses on technological convergence. Gambardella and Torrisi (1998) pioneered the use of the Herfindahl-Hirschman Index (HHI), measuring industrial convergence by calculating the share of technology patents within an industry [25]. Fai and von Tunzelmann (2001) subsequently refined this approach by employing correlation coefficients of patents across industries to assess convergence levels [26]. The input-output analysis method was applied by Guerrieri and Meliciani (2004) to U.S. input-output tables to analyze linkages between producer services and manufacturing [27]. Meng (2023) later extended this method to measure the integration between the digital industry and the industrial sector [8]. Currently, the coupling coordination degree model is a more commonly employed assessment tool. Grounded in industrial synergy theory, it constructs indicator systems for the digital economy and the real economy respectively, and calculates the coupling coordination degree between these two subsystems to reflect the level of integration [5,9].

2.2 Green innovation (GIP)

Unlike traditional innovation, GIP is characterized by its dual attributes of environmental sustainability and technological advancement [5,6]. Chen et al. (2006) defined GIP as the innovation of hardware or software related to green products or processes, including technological advancements in energy conservation, pollution prevention, waste recycling, green product design, and corporate environmental management [28]. Saunila et al. (2018) also emphasized that GIP focuses on resource efficiency and environmental protection, primarily in technology and processes [29]. Some scholars have expanded the scope of GIP beyond product-level advancements to include innovations in processes, services, and management. This broader perspective not only aims to enhance corporate value but also seeks to reduce negative environmental impacts [30], which in turn achieves a harmonious balance of economic, social, and ecological benefits [31].
Academic research on the factors influencing GIP is extensive, with a primary focus on two key areas. The first area includes macro-level factors such as environmental regulations and pollution charges. For instance, Wagner (2007) found that environmental regulations in Germany negatively impacted the number of green patents in manufacturing firms [32]. In contrast, other scholars, such as Li et al. (2016) demonstrated that regulatory pressures, including environmental regulations and pollution charges, positively influence corporate GIP [33,34].

Research has also explored the effects of policies such as digital finance and carbon tariffs on GIP [35,36]. The second area focuses on micro-level factors within enterprises. Studies in this domain have examined how factors such as corporate governance, supply chain management, corporate social responsibility, and leadership capabilities influence GIP [37,38].

2.3 Relationship Between DRI and GIP

Empirical evidence directly linking DRI to GIP remains relatively limited. Existing literature has predominantly focused on the unidirectional effect of the digital economy or digital technologies on green innovation, and these studies can be categorized into three distinct strands for clearer comparison.

First, an efficiency–cost perspective (predominantly positive findings). Most studies have suggested that the digital economy significantly promotes GIP by improving information matching and factor allocation efficiency, reducing search and transaction costs, and facilitating financing and the organization of innovation resources [5,9,11,35]. Recent research has further refined the underlying mechanisms, highlighting channels such as resource allocation efficiency, debt financing costs, industrial-structure coordination, and firm digital transformation. In the YREB context, Luo et al. (2022) also confirmed the positive role of digital development in enhancing green innovation, while noting that the magnitude of this effect varies across cities [7].

Second, a collaboration–network and spillover perspective (emphasizing spatial interdependence). This strand argues that digitalization strengthens platform-enabled coordination, supply-chain linkages, and green knowledge diffusion, thereby fostering green innovation with notable externalities. Spatial-econometric evidence often documents significant spatial spillovers of the digital economy on green innovation (or green innovation efficiency) and industrial green innovation efficiency.

Third, an energy-constraint and nonlinearity perspective (highlighting a potential "green paradox" of digitalization). Beyond the "digital dividend," some studies caution that the energy consumption associated with digital infrastructure construction, equipment operation and maintenance, as well as rebound effects, may offset emission-reduction gains, resulting in diminishing marginal impacts or threshold and nonlinear patterns [39,40]. Related research also finds that digitalization has been more strongly associated with rising energy use at the aggregate level, which urges a more cautious interpretation of its net green effect [41].

In contrast, research explicitly examining the DRI–GIP nexus is still in its nascent stage and remains fragmented across different levels of analysis. A more structured view can be developed by differentiating evidence at the macro–meso–micro levels:

- ***Macro (urban/regional) level:*** Studies have begun to measure DRI using coupling-coordination or composite indices and test its effect on urban green innovation using two-way fixed effects, threshold models, and spatial Durbin specifications, documenting both positive impacts and spillover characteristics [9,42].
- ***Meso (industry/sector) level*:** Based on industrial sector panel data, evidence suggests that DRI can promote industrial green transformation, with mechanisms linked to technological progress and structural optimization [8,24].
- ***Micro (firm) level*:** Closely related evidence at the micro level comes from firm digital transformation, IT–industrialization integration, and the industrial internet. This body of research generally supports the idea that embedding digital technologies into production and management processes enhances both the quantity and quality of green innovation, partly by alleviating financing constraints and information asymmetry [5,43,44].

Overall, while the literature provides useful insights, three gaps remain: (i) the incremental effect of DRI beyond "digital economy" development is not fully disentangled; (ii) competing transmission channels from DRI to GIP have not been systematically compared; and (iii) boundary conditions, spatial spillovers, and within-belt gradients (e.g., the YREB's internal heterogeneity) are still underexplored. Motivated by these gaps, this study offers more systematic evidence on the DRI–GIP nexus at the river-basin scale through mechanism, moderation, and heterogeneity analyses.

1.4 Research Gap and Contributions

While prior research has examined the determinants of GIP and the relationship between the digital economy and GIP, literature specifically investigating the connection between DRI and GIP remains limited. Crucially, the pathways through which DRI influences GIP have not been adequately explored. Therefore, building upon existing literature, this study systematically analyzes the direct impact of DRI on GIP, along with its underlying mediation mechanisms, moderation mechanisms, and effect heterogeneity.

3. Theoretical Analysis and Research Hypotheses

3.1 Direct Impact of DRI on GIP

The advancement of GIP faces significant dual lock-in effects: it is constrained not only by technological lock-in associated with conventional production technologies and capital stocks but also by market lock-in linked to the acceptance of green products and policy continuity [45].

The DRI addresses these challenges through three key theoretical mechanisms. First, from the perspective of new classical growth theory, DRI significantly improves the allocation efficiency of traditional production factors, including capital and labor [46]. This improvement in efficiency releases substantial economic surplus previously trapped in inefficient sectors, thereby creating a valuable resource pool to underpin the high-risk, long-cycle research and development activities that characterize GIP. Second, consistent with endogenous growth theory [47], DRI substantially strengthens knowledge spillover effects. Digital platforms break down geographical and organizational boundaries, facilitating the rapid, low-cost dissemination of green technological knowledge, R&D experience, and best practices across broader domains. This digital-network-facilitated knowledge diffusion significantly reduces the learning costs for latecomer firms, which may accelerate the iteration and widespread adoption of green technologies within the YREB. Finally, from the perspective of transaction cost economics, information asymmetry constitutes a major obstacle to collaborative innovation [48,49]. By leveraging technologies such as big data and blockchain, DRI helps build transparent, traceable information systems that effectively mitigate information asymmetries. This not only reduces the costs associated with searching for partners and evaluating technological solutions but also enables automated execution mechanisms, including smart contracts, thereby expanding the collaborative frontier for GIP.

Within the specific context of the YREB, these direct effects are particularly pronounced. As a key corridor for heavy and chemical industries in China, the region has a heavy industrial structure, faces immense environmental pressure, and undertakes an arduous task of green transformation. Furthermore, spanning eastern, central, and western China, the region exhibits significant internal developmental disparities. DRI can effectively integrate industrial data across the YREB’s upper, middle, and lower reaches, facilitating the intelligent and green upgrading of traditional sectors such as steel and chemicals.

Based on the above analysis, we propose the following hypothesis.

H1: DRI exerts a significant promoting effect on GIP within the YREB.

3.2 Mediating Mechanisms of DRI on GIP

NQP represents an advanced form of productivity that breaks free from dependence on traditional growth paths, essentially characterized by revolutionary technological breakthroughs, innovative allocation of production factors, and in-depth industrial transformation [50]. Through DRI, the in-depth integration of digital technologies such as artificial intelligence and big data into the real economy not only improves production efficiency [10] but also fosters intelligent R&D models and coordinates industrial chains. This directly drives the emergence of disruptive technologies and the optimization of industrial structures [7], thereby positively promoting the formation and development of NQP.

NQP plays a unique role in promoting GIP. First, its core attributes—technological progress and efficiency improvements—significantly lower the research, development, and application costs of green technologies, thereby enhancing the economic feasibility of GIP [51]. Second, NQP’s emphasis on total factor productivity growth requires coordinated development between economic activities and the ecological environment. This inherent green orientation systematically directs innovation resources to green technology sectors [52]. Finally, within the YREB, the development of NQP is reshaping the regional industrial landscape. Industrial clusters such as smart manufacturing in the Yangtze River Delta, electronic information in the Chengdu-Chongqing region, and optoelectronics in Wuhan all exhibit strong GIP vitality. This trend is transforming GIP from an external constraint into a strategic choice for firms pursuing high-quality development. Thus, we propose the following hypothesis.

H2: NQP plays a positive mediating role in the impact of DRI on GIP.

3.3 Moderating Mechanisms of DRI on GI

3.3.1 The Moderating Role of Environmental Regulation (ENR)

The overarching principle guiding the development of the YREB is “prioritizing ecological protection over large-scale development.” This strategic orientation is reinforced by a robust environmental regulatory framework that includes central environmental inspections and the Yangtze River Protection Law, which provides an ideal context for examining the Porter Hypothesis [53]. Within this institutional context, ENR enhances the impact of DRI on GIP through multiple pathways. First, it generates a demand-pull effect: stringent emission standards compel firms to prioritize the application of DRI outcomes in areas such as energy conservation and emission reduction [7]. Second, it generates an innovation compensation effect: compliance-related cost savings, such as reductions in carbon taxes, along with potential brand premiums, can transform GIP from a cost center into a profit center [54]. Third, it generates a risk reduction effect: the stable policy expectations stemming from the "prioritizing protection" strategy reduce the institutional risks perceived by firms, which in turn encourages long-term R&D investments in green technologies.

Based on the above analysis, we propose the following hypothesis.

H3: ENR plays a positive moderating role in the relationship between DRI and GIP.

3.3.2 The Moderating Role of Local Government Competition (LGC)

Within China's fiscal decentralization system, LGC has long been centered on GDP growth as its primary goal. Since 2012, with the inclusion of ecological civilization construction in the performance evaluation system, the logic of inter-local competition has gradually shifted from a singular focus on economic growth to embracing multi-dimensional goals, including ecological performance. This shift is particularly evident in the YREB, where the overarching strategy of "prioritizing ecological protection and pursuing green development" has driven institutional and policy innovations focused on green and low-carbon development. Cities are competing to position themselves as smart cities, zero-waste cities, and dual-carbon demonstration zones, and implementing specialized support policies. Such benign competition not only enhances the institutional environment for green digital projects but also promotes the cross-regional flow of innovative factors, including technology, capital, and talent [55]. This, in turn, helps amplify the incentive effect of DRI on GIP. On the one hand, local governments adopt measures such as fiscal subsidies, land use guarantees, and data openness to reduce the costs for firms engaged in digital and green transitions [56]. On the other hand, demonstration practices in more advanced regions speed up the diffusion of green digital governance experiences to midstream and upstream cities [57], thereby improving overall synergistic efficiency.

Consequently, LGC—instead of merely triggering a race to the bottom—acts under institutional constraints and learning mechanisms as a significant contextual condition that magnifies the green effects of DRI.

Based on the above analysis, the following hypothesis is proposed.

H4: LGC plays a positive moderating role in the relationship between DRI and GIP.

3.3.3 The Moderating Role of Government Digital Attention (GEA)

The allocation of government attention is a key prerequisite for scientific decision-making and effective governance [58]. Within China's decentralization framework and central-local relations, local governments face multiple policy objectives and performance constraints; their attention allocation shapes the choice of policy instruments and resource allocation, which in turn influences firms' expectations and innovation behaviors [59,60]. From the perspective of the attention-based view, organizational actions, including those of governments are driven by the direction of limited attention toward certain issues, a process that may strengthen selected agendas while crowding out attention and resources from other equally important areas [61]. Accordingly, when government digital attention (GDA) is excessively focused on "digital economy or digital industry" agendas, it may diminish the marginal benefits of digital-real integration (DRI) to green innovation performance (GIP).

First, specifically, the negative moderating effect of GDA may operate through three channels:

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Target bias and resource crowding-out. When local governments prioritize highly visible, fast-return digital agendas (such as digital-economy hubs, digital government and smart cities, computing-power and data-center projects), scarce fiscal funds, land quotas, credit support, and talent policies may be allocated disproportionately to digital projects. This crowds out firms' long-term green R&D investments and experimental space. This "digital-first, green-constrained" resource reallocation can weaken the actual positive impact of DRI on GIP [61,62].

Second, administrative intervention and strategic innovation. When digitalization indicators and earmarked funds become key performance levers, governments may steer firms' technology choices through administrative guidance or subsidy bias, thereby shifting innovation toward policy-aligned trajectories rather than market-driven green technologies [59,61,62]. Meanwhile, stronger policy support may lead to strategic (symbolic) innovation, where firms prioritize label-driven projects to secure subsidies and preferential resources replacing substantive green technological breakthroughs with mere formal compliance [62].

Third, policy uncertainty and investment delay. Rapid digital technology iteration and frequent regulatory and policy adjustments may increase policy uncertainty, which strengthens firms' real-options "wait-and-see" incentives and deters long-cycle, high-cost, and more irreversible green R&D investment [63,64]. Prior studies have documented that policy uncertainty inhibits investment and innovation; in the green sector, uncertainty surrounding subsidy policies can also reduce firms' green R&D and inputs into green innovation [64,65].

H5: GDA plays a negative moderating role in the relationship between DRI and GIP. The conceptual framework for the empirical analysis is shown in Fig 1.

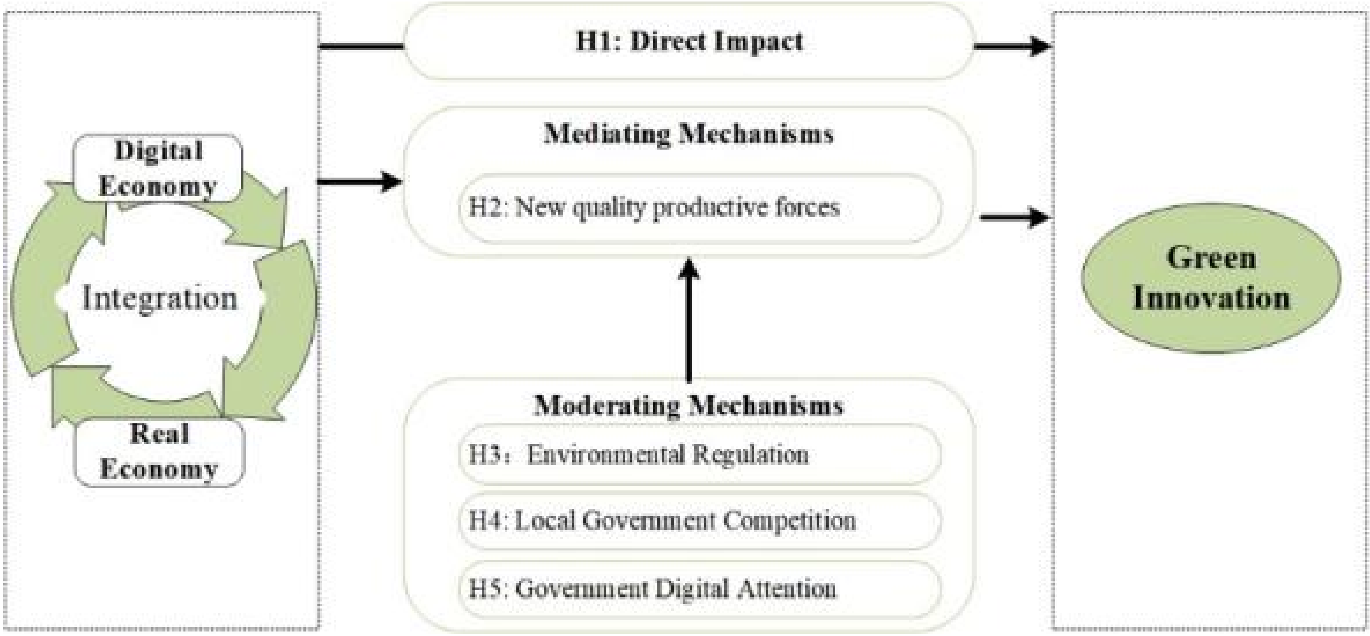

Fig 1. Conceptual framework for the empirical analysis

4. Empirical Research Design

4.1 Variable Selection

4.1.1 Core Explanatory Variable (DRI)

DRI involves an interactive association between two subsystems: the digital economy and the real economy. To measure the degree of this integration, this study adopts the methodologies proposed by Sun et al. (2024) and Liu et al. (2024), using a coupling coordination degree model to quantify DRI [5,9]. This measurement requires a prior assessment of the development status of both component subsystems.

For the Digital Economy subsystem (De), this study adopts the framework developed by Zhao et al. (2022), which includes indicators such as internet penetration rate, the number of employees in internet-related industries, the size of the mobile internet market, internet-related output, and the development of inclusive digital finance [66]. Regarding the Real Economy subsystem (Re), and taking into account data availability constraints at the municipal level, this study adopts the approach proposed by Xu et al. (2025) and Huang et al. (2024). This framework assesses the development level of the real economy from three dimensions: development scale, structural characteristics, and economic benefits [42,67]. Details of the hierarchical indicators are presented in Table 1

Table 1 Evaluation index system for the digital economy subsystem and the real economy subsystem

First-Level Indicator	Second-Level Indicator	Third-Level Indicator
De	Internet Penetration Rate	Number of Internet Users per Hundred People
	Number of Internet-Related Employees	Computer Services and Software Employees to Total

		Employees Ratio
	Internet-Related Output	Telecommunications Business Volume per Capita
	Mobile Internet Market Size	Number of Mobile Phone Users per Hundred People
	Inclusive Development of Digital Finance	China Digital Inclusive Finance Index
Re	Development Scale	Value Added of the Secondary Industry to GDP
		Total Retail Sales of Consumer Goods to GDP
	Development Structure	Non-Agricultural Employees to Total Employees Ratio
	Economic Benefits	Profits of Large-Scale Industrial Enterprises to Sales Revenue

After establishing the assessment framework for De and Re, the entropy method is used to calculate the development levels of the two subsystems [68], respectively. With the measured development levels of both subsystems, the Coupling Coordination Degree Model (Equations 1 and 2) is then utilized to further determine the level of DRI in the YREB, referred to as DRI:

$$C_{dr} = 2\sqrt{De \times \mathrm{Re}} / (De + \mathrm{Re}) \quad (1)$$

$$DRI = \sqrt{C_{dr} \times (\alpha De + \beta \mathrm{Re})} \quad (2)$$

In Equation (2), α and β denote the weights of the digital and real economies, respectively, with the condition α + β = 1. For this paper, it is set that both α and β are assigned the value of 0.5 [68].

4.1.2 Dependent Variable (GIP)

Following prior established literature (Li et al., 2024), we measure GIP activity by using the total number of green patent applications at the city level. The data are obtained from the Green Patent Classification Database of the China National Intellectual Property Administration. To address the issues of right-skewed distribution and heteroscedasticity, the raw application data are transformed through the natural logarithm after adding 1.

4.1.3 Mediating Variables: New quality productive forces (NQP)

To avoid potential overlap with indicators already incorporated into the DRI evaluation system, this study uses the frequency proportion of NQP-related expressions in local government work reports as a proxy for NQP. As " new quality productive forces" first emerged in Chinese policy agenda and governance discourse as a policy-driven concept, government work reports can effectively reflect local governments' attention to this development direction and their corresponding policy supply orientation. Based on the conceptualization of NQP proposed by Zhou et al. (2023) [69], we construct a keyword dictionary covering three dimensions: frontier technologies and innovation breakthroughs, industrial forms and structural upgrading, and high-quality development and efficiency improvement. We then employ text-based measurement on government work reports to capture regional-level NQP.1

4.1.4 Moderating Variables

Environmental Regulation (ENR): Following Meng et al. (2024), we perform textual analysis on government work reports of prefecture-level cities. The intensity of environmental regulation is proxied by the frequency of keywords including environmental protection, pollution control, and other related terms, as a proportion of the total text length [42,70,71].

Local Government Competition (LGC): This indicator captures the catch-up behavior of local officials motivated by performance evaluation under China's fiscal decentralization system. As the evaluation system places growing emphasis on green and low-carbon development, the competition paradigm has shifted from a singular focus on GDP growth to the integration of sustainable development objectives. Following the method proposed by Yue and Han (2025), the competition index is constructed based on the lead of a locality's economic growth rate over its neighboring regions. A higher value signifies a stronger sense of development urgency and more intense competitive activities [60].

Government Digital Attention (GDA): The annual average search frequency of keywords including digital economy and digital transformation for each prefecture-level city in the Baidu Index is employed as a proxy variable [72,73]. This measure captures local governments' policy focus and public attention towards digital development initiatives.

4.1.5 Control Variables

To mitigate potential omitted variable bias, we choose a series of control variables commonly employed in prior studies, encompassing economic level, population density, openness to foreign investment, urbanization rate, financial development level, and educational expenditure.

Economic Density (ECO): Economic level is measured as the ratio of regional GDP to the land area of the administrative jurisdiction, which is then transformed through the natural logarithm [42].

Population Size (POP): Population density is represented by the natural logarithm of the registered population, which controls for the impact of population size on innovation activities [9].

Financial Development Level (FIN): It is measured as the year-end balance of deposits and loans of financial institutions as a proportion of regional GDP, which reflects the regional financial support capacity.

Openness Level (OPE): Calculated as the ratio of actually utilized foreign direct investment to regional GDP [8,9].

Urbanization Rate (URB): Urbanization rate is defined as the proportion of the non-agricultural registered population to the total registered population, which captures the agglomeration effects and environmental pressures related to urbanization.

Educational Investment Level (EDU): Educational expenditure is represented as the proportion of local government educational expenditure in the general public budget expenditure, which reflects the foundational role of human capital accumulation in supporting innovation activities.

4.2 Model Specification

4.2.1 Direct Effect

To examine the direct impact of DRI on GIP in the YREB (H1), the following baseline model is constructed:

$$GIP_{it} = \alpha_0 + \alpha_1 DRI_{it} + \alpha_2 C_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{3}$$

In Equation (3), GIP_{it} represents the GIP level of city i in year t, DRI_{it} denotes the DRI level of city i in year t, and C_{it} is a vector of control variables. The terms μ_i and δ_t represent city and year fixed effects, respectively, and ε_{it} is the random error term.

4.2.2 Mediation Effect

To verify the mediation effects (H2), mediation models are built upon Equation (3):

$$Me_{it}=\beta_0+\beta_1 DRI_{it}+\beta_2 C_{it}+\mu_i+\varepsilon_{it} \tag{4}$$

$$GIP_{it}=\gamma_0+\gamma_1 DRI_{it}+\gamma_2 Me_{it}+\gamma_3 C_{it}+\mu_i+\delta_t+\varepsilon_{it} \tag{5}$$

In Equations (4) and (5), Me_{it} represents the mediating variable. All other variables are defined consistently with Equation (3).

4.2.3 Moderation Effect

To investigate the moderation effects (H3-H5), interaction terms between DRI and the moderating variables are incorporated into Equation (3), establishing the following moderation model:

$$GIP_{it}=\sigma_0+\sigma_1 DRI_{it}+\sigma_2 Mo_{it}+\sigma_3 DRI_{it}\times Mo_{it}+\sigma_4 C_{it}+\mu_i+\delta_t+\varepsilon_{it} \tag{6}$$

In Equation (6), Mo_{it} represents the moderating variable, and $DRI_{it}\times Mo_{it}$ is the interaction term between the core explanatory variable and the moderating variable. All other variable definitions remain consistent with Equation (3).

4.3 Data Sources and Descriptive Statistics

The data for DRI are obtained from the measurements described in the preceding sections. The data for GIP are obtained from the China National Intellectual Property Administration. Other relevant data are collected from sources such as the China City Statistical Yearbook and various local statistical bulletins. The descriptive statistics for all variables are provided in detail in Table 2.

Table 2 Descriptive Statistics of Variables

Variable	N	Mean	SD	Min	p50	Max
GIP	1155	5.402	1.660	1.099	5.283	9.876
DRI	1155	0.312	0.081	0.143	0.294	0.610
ECO	1155	7.562	1.089	4.432	7.463	11.13
POP	1155	6.046	0.615	4.301	6.131	8.136
FIN	1155	2.458	0.959	0.764	2.254	6.559
OPE	1155	0.003	0.003	0.000	0.002	0.014

URB	1155	0.334	0.176	0.0752	0.287	0.996
EDU	1155	0.173	0.030	0.044	0.171	0.267

5. Analysis of Empirical Results

5.1 Direct Effects

5.1.1 Baseline Regression Results

Table 3 reports the baseline regression results for the impact of DRI on GIP. Column (1) presents the results of the baseline model, which includes only the core explanatory variable. Column (2) adds the series of control variables to the model from Column (1). Columns (3) to (5) sequentially adopt ordinary standard errors, robust standard errors, and standard errors clustered at the city-year level.

In Column (5), the estimated coefficient of DRI is 2.148, which is statistically significant at the 1% level. This indicates that a one-unit increase in DRI leads to a significant 2.148-unit increase in a city's GIP, confirming the direct promotional effect of DRI on GIP. Thus, Hypothesis 1 (H1) is supported.

Table 3 Baseline Regression Results

Variables	(1)	(2)	(3)	(4)	(5)
	GIP	GIP	GIP	GIP	GIP
DRI	15.980***	5.027***	2.148***	2.148***	2.148***
	(42.359)	(10.216)	(3.374)	(3.599)	(3.599)
ECO		0.756***	0.771***	0.771***	0.771***
		(19.766)	(7.385)	(7.656)	(7.656)
POP		0.760***	0.315	0.315	0.315
		(20.073)	(1.570)	(1.632)	(1.632)
FIN		0.290***	0.129***	0.129***	0.129***
		(10.072)	(2.830)	(2.850)	(2.850)
OPE		28.513***	3.956	3.956	3.956
		(3.505)	(0.462)	(0.457)	(0.457)
URB		-0.314*	-0.192	-0.192	-0.192
		(-1.815)	(-0.677)	(-0.672)	(-0.672)
EDU		-4.691***	-0.664	-0.664	-0.664
		(-6.277)	(-1.065)	(-1.084)	(-1.084)
City fixed	No	Yes	Yes	Yes	Yes
Year fixed	No	Yes	Yes	Yes	Yes
_cons	0.422***	-6.361***	-3.154*	-3.154*	-3.154*
	(3.476)	(-24.960)	(-1.832)	(-1.820)	(-1.820)
N	1155	1155	1155	1155	1155
R^2	0.609	0.828	0.973	0.973	0.973
* p < 0.1, ** p < 0.05, *** p < 0.01					

5.1.2 Robustness Checks

First, replacing the Explanatory Variable: An alternative DRI indicator (DRIP) was developed at the technology fusion dimension based on patent citation data. As shown in Column (1) of Table 4, the estimated coefficient of DRIP on GIP is 0.038, which is statistically significant at the 5% level, confirming that Hypothesis 1 (H1) remains robust.

Second, Replacing the Dependent Variable: The measure of GIP was substituted with the number of green invention patent applications (GIP1). As presented in Column (2) of Table 4, the results show that the estimated coefficient of DRI on GIP1 is 3.007 and remains statistically significant, which confirms that this robustness check is passed.

Third, Adjusting the Sample Range: Considering the potential structural impact of the COVID-19 pandemic on innovation activities after 2020, we re-estimated the model based on the 2011–2019 sub-sample [74]. As shown in Column (3) of Table 4, the results indicate no significant change in the direction or statistical significance of the coefficient of the core explanatory variable, which further confirms the robustness of the baseline results.

Table 4 Robustness Check Results

Variables	(1)	(3)
	GIP	GIP
DRIP	0.038**	
	(2.322)	
DRI		2.101***
		(3.067)
_cons	-3.077*	-1.054
	(-1.774)	(-0.477)
Control	Yes	Yes
City fixed	Yes	Yes
Year fixed	Yes	Yes
N	1155	945
R^2	0.973	0.973
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$		

5.1.3 Endogeneity Tests

To address potential empirical endogeneity concerns between DRI and GIP, this study adopts an instrumental variable (IV) approach. We chose robot installation density (Rob) and the one-period lagged term of DRI (L.DRI) as instrumental variables. As reported in Table 5, the relevant test findings are presented in detail.

First, using Robot Installation Density as the IV: The first-stage results in Column (1) reveal a statistically significant coefficient of Rob on DRI at the 1% level, which satisfies the relevance condition. The Kleibergen-Paap rk Wald F statistic is 16.997, which is greater than the Stock-Yogo critical value of 16.38. Additionally, the Kleibergen-Paap rk LM statistic is statistically significant at the 1% level, which rejects concerns about weak instruments and underidentification. The second-stage results in Column (2) reveal a DRI coefficient of 9.682 that is statistically significant at the 10% level, which further validates the baseline conclusion.

Second, using the Lagged Term as the IV: The first-stage regression results in Column (3) reveal a coefficient of L.DRI of 0.449, which is statistically significant at the 1% level, which again supports the relevance of the instrument. The weak instrument test F-statistic is 58.165, which is well above the critical value. Moreover, the underidentification test is also passed at the 1% significance level. The second-stage results in Column (4) reveal a DRI coefficient of 5.614 that is statistically significant at the 1% level, which further confirms the promotional effect of DRI on GIP.

Synthesizing the results from both instrumental variable tests, the core findings of this study remain valid after controlling for potential endogeneity, providing further support for hypothesis H1.

Table 5 Endogeneity Test Results

Variables	(1)	(2)	(3)	(4)
	DRI	GIP	DRI	GIP
DRI		9.682*		5.614***
		(1.664)		(3.700)
rob	-0.001***			
	(-4.123)			
L.DRI			0.449***	
			(7.627)	
_cons	0.314***		0.051	
	(3.098)		(0.508)	
Control	Yes	Yes	Yes	Yes

City fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
N	1,155	1,155	1,050	1,050
F statistic	17.00		58.17	
Kleibergen-Paap rk LM statistic	18.139		81.071	
Kleibergen-Paap rk Wald F statistic	16.997		58.165	
* p < 0.1, ** p < 0.05, *** p < 0.01				

5.2 Analysis of Mediation Effect Test Results

Table 6 reports the test results for the mediation effects, where Column (1) presents the baseline regression results. Columns (2) to (3) investigate the mediating path through NQP. Column (2) reveals that the coefficient of DRI on NQP is 0.459, which is statistically significant at the 5% level. In Column (3), the coefficients of both DRI (2.063) and NQP (0.184) are statistically significant. This confirms that NQP plays a positive mediating role in the relationship between DRI and GIP. This mechanism is clearly reflected within the Yangtze River Economic Belt (YREB). The Yangtze River Delta region, by virtue of its robust digital industry clusters, is accelerating the formation of an NQP paradigm that integrates intelligent and green manufacturing. Meanwhile, the Chengdu-Chongqing Economic Zone leverages its big data advantages to promote the intelligent and low-carbon transformation of traditional industries. The inherent green orientation of this advanced form of productivity systematically channels innovation resources toward green and low-carbon sectors (Shi et al., 2023), thereby ultimately improving GIP output. Thus, Hypothesis 2 (H2) is confirmed.

Table 6 Mediation Effect Test Results

Variables	(1)	(2)	(3)
	GIP	NQP	GIP
DRI	2.148***	0.459**	2.063***
	(3.599)	(2.039)	(3.465)
NQP			0.184**
			(2.008)
RMI			
_cons	-3.154*	-0.254	-3.107*
	(-1.820)	(-0.419)	(-1.797)
Control	Yes	Yes	Yes
City fixed	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes
N	1155	1155	1155
R^2	0.973	0.551	0.973
* p < 0.1, ** p < 0.05, *** p < 0.01			

5.3 Analysis of Moderating Effect Test Results

Table 7 reports the test results for the moderating effects. As shown in Column (1) of Table 7, the results reveal that the coefficient of the interaction term (DRI×ENV) is 2.214, which is statistically significant. This confirms that within the strategic context of prioritizing ecological protection in the YREB, stringent environmental regulation (ENV) effectively channels the outcomes of DRI toward GIP-related fields. Thus, Hypothesis 3 (H3) is supported.

As indicated in Column (2) of Table 7, the coefficient of the interaction term (DRI×LGC) is 0.040, which is statistically significant, indicating that LGC exerts a positive moderating effect on the relationship between DRI and GIP. This finding implies that, under the guidance of the YREB development strategy, provincial and municipal governments along the river have introduced supportive policies and strived to establish regional models for the synergistic development of DRI and GIP. This benign competitive landscape significantly

enhances the innovation effectiveness of DRI. Thus, Hypothesis 4 (H4) is validated.
As demonstrated in Column (3) of Table 7, the coefficient of the interaction term (DRI×GDA) is -4.747, which is statistically significant, indicating that GDA plays a negative moderating role. This suggests that excessive government intervention in the DRI process may distort market signals via administrative intervention, thereby potentially suppressing firms' autonomous innovation vitality. The phenomenon of digital performance-oriented projects observed in some parts of the YREB partially supports this finding. Thus, Hypothesis 5 (H5) is confirmed.

Table 7 Moderating Effect Test Results

Variables	(1)	(2)	(3)
	GIP	GIP	GIP
DRI×ENV	2.214**		
	(1.968)		
DRI×LGC		0.040***	
		(5.450)	
DRI×GDA			-4.747***
			(-5.850)
Control	Yes	Yes	Yes
City fixed	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes
_cons	-3.328*	-3.418*	-3.322*
	(-1.938)	(-1.950)	(-1.923)
N	1155	1155	1155
R^2	0.973	0.973	0.974
* p < 0.1, ** p < 0.05, *** p < 0.01			

6. Heterogeneity analysis

6.1 Heterogeneity by Central City Status

Columns (1) and (2) present results classified by whether a city is designated as a central city, which are defined as provincial capitals, sub-provincial cities, or municipalities directly under the central government. In Column (2), the coefficient of DRI for non-central cities is 1.969 and statistically significant, a finding that challenges the conventional core-periphery theory. This finding highlights the inclusive and democratizing potentialities of digital technologies. Within the YREB, peripheral cities such as Yichang and Wuhu have successfully surmounted geographic and institutional disadvantages by virtue of their in-depth integration into the region's digital industrial corridor, thereby achieving remarkable progress in GIP. By comparison, core cities often face structural rigidities and entrenched innovation paths, which restrict the marginal returns of DRI.

6.2 Heterogeneity by Entrepreneurial Activity

Columns (3) and (4) investigate heterogeneity classified by local entrepreneurial dynamism. In Column (5) of Table 7, where entrepreneurial activity is relatively low—which is common in the middle and upper reaches of the Yangtze River—the coefficient of DRI is 2.661, which is statistically significant. This suggests that DRI compensates for deficits in physical entrepreneurial ecosystems by virtue of enabling virtual innovation platforms that lower entry barriers and facilitate cross-organizational collaboration. Such digital infrastructure provides novel organizational forms for green technological breakthroughs (Nambisan, 2017). By contrast, in regions with high entrepreneurial activity, problems such as scattered and fragmented innovation resources and redundant competition may attenuate the marginal impact of DRI.

Table 8 Heterogeneity Analysis Results

Variables	(1)	(2)	(3)	(4)
	Central Cities	Non-central Cities	High Entrepreneurial Activity	Low Entrepreneurial Activity
	GIP	GIP	GIP	GIP

DRI	0.949	1.969**	-0.217	2.661***
	(1.294)	(2.543)	(-0.322)	(2.722)
Control	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
_cons	-6.615	-5.630***	6.224*	-6.077**
	(-1.322)	(-2.867)	(1.808)	(-2.053)
N	132	1023	411	723
R^2	0.979	0.962	0.987	0.960
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$				

7. Discussion

7.1 Research Conclusions

Using panel data from 105 prefecture-level cities in the Yangtze River Economic Belt (YREB) spanning 2011 to 2021, this study systematically explores the mechanisms through which DRI influences GIP. The main findings are summarized as follows. First, quantitative analysis indicates that DRI in the YREB has entered an intermediate stage of development and maintains a positive growth trend, yet there remains considerable potential for further improvement in the overall integration level. Notable regional disparities exist, with the integration level showing a gradual decreasing trend from the downstream to the midstream and upstream regions. Second, empirical results confirm that DRI significantly promotes GIP, a conclusion that remains valid after addressing endogeneity concerns and conducting a series of robustness tests. Mechanism analysis shows that new quality productive forces (NQP) play a positive mediating role between DRI and GIP. Moderating effect analysis indicates that both environmental regulation (ENR) and local government competition (LGC) enhance the positive impact of DRI on GIP. In contrast, government digital attention (GDA) exerts a significant negative moderating effect, indicating that excessive administrative intervention may dampen the GIP vitality of market entities. Furthermore, heterogeneity analysis shows that the promotional effect of DRI on GIP is more pronounced in non-central cities and regions with low entrepreneurial dynamism. This highlights its unique value in advancing regional coordination and mitigating green development imbalances.

7.2 Policy Implications

Drawing on our findings—including that DRI promotes GIP through two key channels: (i) enhancing new quality productive forces (NQP) and (ii) mitigating resource misallocation that environmental regulation (ENR) and local government competition (LGC) enhance this promotional effect while excessive government digital attention (GDA) may weaken it, and that the impacts of DRI on GIP vary across the upper, middle, and lower reaches of the Yangtze River Economic Belt (YREB) as well as across different city types, we propose the following region-differentiated and instrument-targeted policy implications.

7.2.1 A tiered DRI implementation roadmap: Downstream “ In-Depth Application ”, Midstream “ Systematic Upgrading ”, and Upstream “ Capacity Building ”

Downstream (Yangtze River Delta): The focus should shift from infrastructure expansion to scenario-driven adoption and standards-based governance. Leveraging chain-leading firms and industrial parks, efforts should be made to scale up industrial internet platforms and digital twin applications in fields such as green manufacturing, energy management, and low-carbon logistics. Meanwhile, compliant data circulation mechanisms and green data standards (e.g., carbon accounting protocols and product carbon footprint data interfaces) should be developed to disseminate replicable solutions to upstream and midstream regions.

Instruments: Scenario-based pilots (mission-oriented programs), industry standards and interface specifications, green procurement policies and “first-of-its-kind” supportive measures, as well as park-level DRI demonstration evaluation and assessment, should be promoted to advance the in-depth application of DRI in the downstream region.

Midstream (Mid-Yangtze): Priority should be given to the integration of digital retrofitting of manufacturing and green process upgrading. An integrated scheme combining digital transformation vouchers for small and medium-sized enterprises (SMEs) and interest subsidies for green upgrading should be established to encourage the retrofitting of smart energy-saving equipment, online energy monitoring, and the upgrading of process control systems.

Instruments: Transformation vouchers, interest subsidies, energy performance contracting (EPC) coupled with digital monitoring, and standardized diagnostic service packages.

Upstream (Chengdu–Chongqing and upper reaches): The primary focus should be on filling the gaps in industrial-side foundational capabilities, such as industrial internet access, computing and edge nodes, as well as sensing and data collection systems. Efforts should start with modular, low-cost, and replicable retrofitting initiatives, while avoiding " one-size-fits-all" large-scale projects.

Instruments: Regional industrial internet public service platforms, "rent instead of build" for computing/edge capacity, park-level unified low-cost SaaS deployment, phased acceptance linked to energy-intensity reduction and green patent outputs.

7.2.2 Operationalize the "NQP–green innovation" linkage via an industry–technology–talent–finance policy package

Given that NQP is a key transmission channel, policies should translate NQPF cultivation into actionable packages.

Downstream: promote joint "digital + green" breakthroughs in smart manufacturing, clean-energy equipment, low-carbon materials, and green supply-chain software, with incentives tilted toward high-quality green invention patents and standards.

Instruments: mission-oriented R&D programs, firm-led university–industry consortia, rewards based on patent quality (e.g., invention patents/highly cited patents).

Midstream: support upgrading in incumbent industries (steel, chemicals, building materials, automotive) through green process packages and industrial software substitution to create scalable technical roadmaps.

Instruments: common-technology platforms, catalogues of green process packages, combined subsidies and super deductions for software substitution and green upgrading.

Upstream: emphasize application-oriented innovation and engineering deployment to lower trial-and-error costs for green technologies.

Instruments: first-batch application subsidies, demonstration insurance/compensation, "engineer-in-factory + digital diagnosis" services for SMEs.

7.2.3 Improve environmental regulation and government competition: compete on green outcomes, not digital metrics, and reduce administrative crowding-out

Performance metric redesign: bind DRI performance with green innovation outcomes and reduce competition over simple digital-project counts. Include indicators such as green patent quality, carbon intensity reduction, and green TFP improvements, with differentiated weights across upper–middle–lower reaches.

From picking technologies to setting rules and incentives: rely more on standards, market mechanisms, and outcome-based subsidies, avoiding direct administrative intervention in firms' technology pathways and preventing "digital vanity projects" from crowding out market-driven innovation.

Instruments: pay-for-performance, ex-post subsidies, third-party verification and standards, negative-list governance.

7.3 Limitations and Future Research

While this study has adopted multiple methods to ensure the robustness of its conclusions, several limitations persist, which also point to directions for future research.

First, in the moderating effect analysis, there may be a potential bidirectional causal relationship between Government Digital Attention (GDA) and green innovation. For instance, regions with active green innovation activities may naturally attach greater importance to digital topics. This demand-induced endogeneity may compromise the precise estimation of the moderating effect. Although this study provides robust theoretical reasoning and its core findings remain consistent across multiple model specifications, future research could more rigorously identify the net moderating effect of GDA by adopting more exogenous instrumental variables (e.g., the promotion intensity of higher-level digital policies) or quasi-experimental designs.

Second, the mechanism tests are of an indirect nature. While this study provides robust statistical evidence for the theoretical mechanisms via mediation effect models (i.e., enhancing New Quality Productive Forces, NQP), these tests remain indirect validations relying on city-level macro data. Future research integrating firm-level micro-data, policy text analysis, or case studies could more directly uncover the micro-causal chain between technological penetration, organizational change, and green innovation behavior during the DRI process.

Finally, the findings are limited by their external validity and failure to capture dynamic characteristics. This study focuses on the Yangtze River Economic Belt (YREB), a specific national strategic region. Its conclusions are informative for similar river basin economies worldwide at comparable development stages and under similar policy contexts, but caution is warranted when generalizing to other institutional and cultural settings. Moreover, both DRI and green innovation are dynamically evolving processes. The cross-sectional observations based on data spanning 2011 to 2021 in this study fail to fully capture the long-term nonlinear relationships between them and their stage-specific characteristics. Future studies could extend the observation period or adopt models capable of capturing dynamic interactions, such as the Panel Vector Autoregression (PVAR) model, for supplementary analysis.

Ethics approval and consent to participate

Ethics approval was not applicable. This study did not involve any human participants or animal subjects.

Data availability statement

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding

First, Chongqing Municipal Social Science Planning Program: Research on the Mechanism of AI-Driven Co-Benefits of Pollution and Carbon Reduction in the Chengdu-Chongqing Economic Circle (2025ZXYB39).

Second, Project of Humanities and Social Sciences Research Base of Chongqing Municipal Education Commission: Research on the Pathways for Advanced Manufacturing Clusters to Promote Resilience Governance in Chongqing Megacity (25SKJD227).

Third, Chongqing Education Science Planning Project (Youth Project, 2025): Research on the Collaborative Governance of Industry-Education Integration in Application-Oriented Undergraduate Universities under Digital-Intelligent Transformation (K25YY2210049).

List of Abbreviations

Abbreviation	Definition
DRI	Digital-Real Integration
GIP	Green Innovation
YREB	Yangtze River Economic Belt
NQP	New Quality Productive Forces
ENR	Environmental Regulation
LGC	Local Government Competition
GDA	Government Digital Attention

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