

Article

The Synergistic Effect of Digital Industry Agglomeration and Digital–Intelligent Technology on Green Productivity: An Internal–External Coordination Perspective on Innovation Resources

Shuo Liu * and Hongyu He *

School of Economics, Shenyang University, Shenyang 110003, China

* Correspondence: liushuo@syu.edu.cn (S.L.); hehongyu@syu.edu.cn (H.H.)

Abstract

In the digital economy era, the interaction between digital industry agglomeration (DIA) and digital–intelligent technology application (DIT) is pivotal for enhancing green productivity (GP). This study evaluates GP across three dimensions: labourers, means of labour, and objects of labour. Adopting both the external perspective of regional innovation resources and the internal perspective of enterprise innovation allocation, the research applies simultaneous equation models, moderated mediation models, threshold models, and spatial Durbin models to assess how DIA–DIT synergy affects GP. The findings are as follows: (1) DIA and DIT reinforce each other by combining external resource provision with internal resource orchestration, which reduces innovation resource misallocation and promotes GP, with knowledge breadth amplifying this effect. (2) The positive effect of DIA–DIT synergy on GP shows diminishing marginal returns beyond a certain synergy threshold; by contrast, when regional knowledge breadth and innovation exceed their respective thresholds, their favourable impact on GP is amplified. (3) The spatial spillover of this synergy on GP varies with development stage: in less developed regions, DIA–DIT synergy yields a positive spatial spillover for GP, while in developed regions it produces a negative spillover for neighbouring areas. Overcoming these threshold constraints and harnessing spatial spillovers are therefore essential to foster coordinated development and realise the full potential of GP.

Keywords: digital industry agglomeration; digital–intelligent technologies; synergy



Academic Editor: Maria Palazzo

Received: 23 April 2026

Revised: 15 June 2026

Accepted: 17 June 2026

Published: 9 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Green productivity (GP) encompasses both green and sustainable productivity. Its essence lies in fostering the concurrent enhancement of economic growth and the quality of the ecological environment, achieved through technological innovation and the harmonious coordination of production factors [1,2]. In recent years, digital–intelligent technology has proliferated globally at an unprecedented rate. The World Bank reports that in 2025, middle-income countries accounted for over 40% of ChatGPT traffic [3]. However, research indicates that the issue lies not with the technology itself but with its adoption and dissemination, as the uptake of advanced digital tools remains well below their potential [4,5]. In this context, the true impetus may stem from the deep integration and coordinated evolution of both digital industry agglomeration (DIA) and digital–intelligent technology application (DIT). As DIT rapidly penetrates various sectors, the spatial organisation of

industrial activities is becoming increasingly intertwined with technical capabilities. When DIA and DIT create a mutually reinforcing synergy, the technological dividend may be effectively harnessed, potentially contributing to a leap in GP.

GP fundamentally relies on innovation. It has the potential to transcend traditional combinations by leveraging advanced elements such as technology, data, and talent, thereby facilitating the harmonious development of economic growth alongside green initiatives. Nevertheless, this process faces global constraints: a shortage of core innovation resources, their uneven geographic distribution, and systemic innovation risks stemming from long cycles and high uncertainty. In response, the synergy between DIA and DIT offers a dual pathway to overcome these constraints. Within this framework, DIA transcends mere spatial concentration of enterprises; it serves as a strategic spatial response to these external constraints and a means to foster GP. Meanwhile, DIT enhances firms' internal resource allocation capabilities, specifically their organisational effectiveness in identifying, absorbing, and recombining internal and external innovation resources to accomplish technological breakthroughs and business model innovations, thereby reducing innovation risks and improving the efficiency of resource utilisation. In other words, the emergence of GP depends not only on the reconstruction of industrial space at the macro level but also on firms' capacity to allocate resources at the micro level. The interaction and coupling of these two dimensions constitute the core mechanism driving leaps in GP.

However, despite the growing adoption of digital technologies, existing studies have largely examined DIA and DIT in isolation, treating them as separate drivers rather than as interacting forces. This fragmented perspective has left a critical theoretical and empirical question unresolved: although digitalisation is widely advocated as a catalyst for sustainable development, it remains unclear how the interplay between spatial industrial dynamics (DIA) and firm-level digital capabilities (DIT) jointly shapes GP, especially in emerging economies. Moreover, the possible mechanisms through which such synergy operates and whether it exhibits nonlinear pathways still await systematic investigation. This oversight may perpetuate the very external constraints that GP seeks to overcome.

China provides a particularly illuminating context for examining these dynamics. As a major economy undergoing a profound digital transition, China has made the "deep integration of the digital and real economies" a national priority. By the end of 2025, China had built 4.838 million 5G base stations, with operational computing power centres housing over 13.73 million racks, thus providing essential support for enhancing DIT. Meanwhile, China has proposed a development framework for GP, which provides a highly valuable quasi-natural experimental environment for this study.

This study explores how the synergy between DIA and DIT affects GP. The findings seek to broaden international understanding of how digitalisation can be strategically leveraged for GP transformation, offering insights relevant to China and to other economies undergoing similar structural transitions.

2. Literature Review

Existing research has predominantly focused on the individual driving effects of DIA and DIT on GP. Regarding DIA and GP, studies indicate that DIA empowers GP through mechanisms such as innovation, radiation, and knowledge spillovers [6–8]. The impact of DIA on green total factor productivity (GTFP) exhibits a U-shaped nonlinear characteristic—initially inhibiting and then promoting—along with negative spatial spillover effects [9]. Similarly, European regional studies have found that ICT-oriented regions are more likely to achieve a twin (digital-green) transition than green-oriented regions [10]. Furthermore, using OECD regional patent data and a spatial Durbin model, Sergio et al. (2023) demonstrate that ICT agglomeration generates significant positive

spatial spillovers on innovation in high-tech sectors, with technological proximity and cross-regional knowledge networks serving as key moderators [11]. This reveals an important transmission pathway from ICT industry agglomeration to technological innovation, and then to the improvement of regional green total factor productivity (GTFP).

Turning to the firm-level perspective, research shows that enterprise-level digital technology application empowers green productivity through mechanisms such as technological innovation, human capital upgrading, and industrial structure transformation [12,13], constituting a core pathway for enhancing firm and industrial green productivity. Moreover, the application of digital technologies at the firm level faces the challenge of the “productivity paradox”, and its value realisation depends on the combination with complementary assets [14,15]. The impact of digital technology application on GP is not simply linear. Studies have found that digital transformation has an inverted U-shaped, nonlinear effect on green innovation [16] and that data factors exhibit an inverted U-shaped relationship with low-carbon development in the manufacturing sector [17,18]. Meanwhile, AI computing power demonstrates a U-shaped relationship with the green transformation of energy enterprises [19], indicating that an optimal range exists for the impact of digital technology application on GP.

However, existing research has not directly addressed the synergistic effects of DIA and DIT on GP. Nevertheless, current studies suggest the logical possibility for such synergy. On one hand, DIA promotes GP through industrial–technology integration mechanisms. Research indicates a nonlinear inverted U-shaped relationship between DIA and carbon productivity, with green technology innovation serving as the core mediating pathway [20]. On the other hand, the effectiveness of the DIT application is conditioned by the external ecosystem. Studies show that a firm’s absorptive capacity is a critical determinant of whether external digital and green technologies translate into emission reductions [6,21,22], and the maturity of the digital innovation ecosystem significantly influences green total factor productivity [23]. Furthermore, the external ecosystem can unlock the enabling potential of digital technologies for green productivity. The talent pools, supply chain networks, common technology platforms, and dense data flow environments formed by DIA are precisely the key factors that reduce firm-level technology application costs and improve the external ecosystem. Research demonstrates that resource allocation efficiency and technological innovation constitute the core mediating pathways through which DIA enables inclusive green growth [24], providing indirect evidence of the critical role of the external environment in unlocking the value of DIT application. Moreover, in the early stages of AI agglomeration, knowledge spillovers primarily occur within the industry; as the industry matures, AI clusters exhibit multi-scalar characteristics that combine local agglomeration with global connectivity [25]. This finding provides support for the argument that DIA–DIT synergy facilitates a transition from geographical agglomeration to network-based clustering. However, the synergistic effects of DIA and DIT on green productivity have yet to be systematically examined.

GP is fundamentally defined by the intrinsic unity of economic growth and environmental protection, with technological innovation serving as its primary driver [1]. At the measurement level, green total factor productivity (GTFP) is widely adopted as the core metric for quantitative assessment [26]. Common methodological approaches include the Malmquist–Luenberger index, the Luenberger–Hicks–Moorsteen productivity indicator, the Luenberger productivity indicator, and parametric methods such as stochastic frontier analysis (SFA) [27,28]. Existing research on the conceptualisation of GP has predominantly focused on three dimensions: technology, economy, and green development, but the dimension of labour factors was not considered.

Thus, although the existing literature indirectly implies the potential for an interdependent synergistic relationship between DIA and DIT, current research predominantly focuses on their individual impacts on GP. This fragmented perspective frequently overlooks the underlying mechanisms that could enhance GP. Accordingly, this study makes three primary contributions. First, this study reconceptualises GP from the multiple perspectives of labourers, means of labour, and objects of labour, building upon existing studies that have focused on the dimensions of technology and green development. Second, it develops and empirically tests a novel analytical framework. Using simultaneous equation and multiple-regression models, we demonstrate the mutual reinforcement between DIA and DIT and show that they synergistically empower GP. Third, it unpacks the mechanisms and boundary conditions of this synergy. Our findings reveal that the DIA–DIT synergy enhances GP by improving innovation-resource allocation, and its effectiveness is contingent on threshold factors (e.g., regional knowledge breadth and self-development) and exhibits spatial spillover effects. This research offers valuable policy insights for other emerging economies in advanced stages of digitalisation. It illustrates how to maximise productivity dividends from digital transformation by optimising the external innovation environment and stimulating enterprises' internal innovation allocation.

3. Theoretical Analysis

3.1. *The Effect of DIA–DIT Synergy on GP: External Enablement and Internal Allocation*

Digital industrial clusters exhibit both digital and spatial attributes [29,30]. Digital technologies have weakened geographical boundaries, shifting economic activities toward virtual networks [31]. Despite these advancements, the economic externalities resulting from geographical proximity still significantly influence economic development through digital affordance [32]. From the perspective of digital and spatial affordances, the coordinated development of DIA and DIT has shaped the distinctive features of digital industrial clusters. As defined in this study, DIA–DIT synergy refers to the interdependent and mutually reinforcing relationship between the geographical concentration of digital industries and firms' in-depth application of digital-intelligent technologies in production, management, and innovation activities.

Most existing studies focus on either the role of DIA or the DIT in influencing GP, often lacking a unified theoretical framework. To bridge this gap, this paper combines external enablement theory [33] with resource orchestration theory [34] into a cohesive analytical framework. This framework examines how the interaction between DIA and DIT affects GP. External empowerment theory posits that DIA, by altering the external environment, provides abundant resources and favourable conditions for enhancing GP. Meanwhile, resource orchestration theory suggests that firms can systematically accumulate, integrate, and transform external resources into value-creating capabilities through three core processes: resource structuring, bundling, and leveraging. Specifically, as an external enabler, DIA offers rich innovation resources, supporting firms in resource structuring, which involves the systematic accumulation and allocation of external resources. DIT encourages firms to combine DIA's external resources with internal capabilities and leverage these combined resources to create value. When the structured provision of external resources and firms' internal orchestration capabilities reinforce each other, a synergy between DIA and DIT emerges, resulting in a system-level advantage that surpasses the sum of their individual effects.

Firstly, DIA facilitates the organised accumulation and distribution of external resources, establishing a strong complementary environment that enhances firms' GP through DIT. Specifically, DIA nurtures a specialised pool of digital talent and enhances the dissemination of high-skill and tacit knowledge. This reduces firms' barriers to accessing

advanced DIT and high-end personnel [35], eliminates external constraints on the flow of innovation resources, and provides human capital for green technology R&D and cleaner production. Simultaneously, data-sharing platforms lower the marginal cost of circulating and utilising innovation resources, thus alleviating external resource constraints on firms' green innovation efforts [36] and enabling them to acquire environmental management data and low-carbon technology information at reduced costs. Moreover, DIA promotes specialised production collaboration among firms by eliminating technological barriers and integrating dispersed industrial data, thereby creating an external enabling mechanism that shares the risks of disruptive innovation and mitigates external constraints on firms' technological advancements [37]. As a result, firms can focus on developing low-emission, high-energy-efficiency production processes, laying the foundation for the systematic accumulation and allocation of external resources.

Secondly, DIT functions as an internal orchestration mechanism, effectively bundling and leveraging resources to transform external inputs into GP. This transformation reduces production costs and enhances capital allocation efficiency, thereby fostering GP [38]. The productivity J-curve [39,40] suggests that DIT's success hinges on the coordinated alignment of technology, organisation, and the external environment. By improving information acquisition and processing, enterprises utilise DIT to convert resources from DIA into internal drivers, guiding the selection of optimal green technology pathways. Through the integration of internal and external innovation resources, firms improve their capacity to allocate innovation inputs [41,42], directing R&D investment towards technological domains with significant emission-reduction potential. Artificial intelligence further enhances the absorption and recombination of internal knowledge, increasing the efficiency with which firms transform externally sourced resources from DIA. This process encourages breakthrough green innovations [43] and provides the technical foundation for zero-carbon processes or circular-economy models. Additionally, DIT streamlines internal workflows and promotes organisational flattening [44], reducing the R&D cycle for green technologies and improving the allocation of innovation resources. Collectively, these effects enhance the bundling and leveraging of firm innovation resources, thereby strengthening GP.

As Milgrom and Roberts (1995) observed, when decisions or assets are adopted synergistically, their combined value surpasses the sum of their individual contributions [45]. Similarly, synergy between DIA and DIT occurs when external structuring (DIA) and internal orchestration (DIT) form a virtuous cycle. This synergy cultivates a digital industry cluster ecosystem, merging the benefits of geographical spillover and network coordination. It reduces the geographical limitations of knowledge spillover while enhancing the spread of green technologies through digital channels. Consequently, it lowers the high costs and uncertainties associated with green innovation, thereby promoting the growth of GP.

H1. *DIA–DIT synergy can significantly enhance GP.*

3.2. The Mediating Mechanism of Innovation Allocation in DIA–DIT Synergy Enabling GP

The crux of developing GP lies in innovation. However, the profit-driven nature of capital and information asymmetry often leads enterprises to prefer low-risk innovation activities [46]. Such excessive caution stifles corporate innovation. Furthermore, the misallocation of innovation resources distorts factor prices and investment returns, hindering the market's ability to direct resources effectively into appropriate innovation areas, thus obstructing efforts to enhance GP. As previously noted, the synergy between DIA and DIT promotes the optimal allocation of innovation resources. This is achieved by strategically distributing both internal and external innovation resources. Externally, the local buzz and the innovation network generated by the digital cluster ecosystem increase the ease of sharing innovation resources [47], thereby lowering implicit costs and information asymmetry

for firms seeking access. Consequently, this diminishes innovation risks and encourages the interdisciplinary flow of innovation resources. Internally, by enhancing their ability to absorb innovation resources, enterprises can more effectively identify high-return innovation opportunities and optimise resource allocation, fostering the emergence of new technologies and business models [48], thereby significantly advancing GP.

Regional knowledge breadth plays a critical role in mitigating the negative impact of innovation-resource misallocation on green productivity. In regions with a broad knowledge base, the diversity of technological domains provides a reservoir of potential combinatorial opportunities [49]. This diversity lowers the marginal cost of identifying and integrating complementary knowledge assets, thereby enabling a more efficient reallocation of R&D resources from low- to high-productivity uses. Furthermore, within such diversified innovation ecosystems, collaborative networks spanning different knowledge fields reduce the coordination costs and trial-and-error inefficiencies typically associated with cross-sectoral partnerships [50]. The reduced cost of resource reallocation, in turn, accelerates the diffusion of novel solutions, ultimately mitigating the growth-suppressing effect of resource misallocation on green productivity.

H2. *DIA–DIT synergy fosters GP by reducing innovation-resource misallocation, while regional knowledge breadth mitigates the impact of this misallocation on GP.*

3.3. The Threshold Effect of DIA–DIT Synergy on GP

There is an optimal scale for the economic benefits of industrial agglomeration, as excessive concentration can harm economic development [51]. Although DIA–DIT synergy can reduce information silos through a coordinated network and thus temper the negative externalities of DIA, a threshold effect on GP remains. As synergy deepens, frequent data exchange and cross-organisational collaboration raise coordination costs for firms and complicate governmental data oversight; once the synergy level passes a certain point, marginal costs outweigh marginal benefits and net gains decline. In a highly synergistic digital ecosystem, excessive geographical and cognitive proximity also risks regional lock-in and knowledge homogenisation [52]. Moreover, studies find that the effect of the scope and breadth of firms' external knowledge search on innovation performance follows an inverted U-shape, because excessive search imposes managerial burdens and distractions that inhibit innovation [53]. Thus, although DIA–DIT synergy speeds information flows, it can encourage excessive knowledge search by firms and so weaken improvements in GP. When synergy exceeds its optimum, negative effects emerge, and the balance of positive and negative forces reduces the enhancement of GP. Figure 1 presents the theoretical analysis framework of this study.

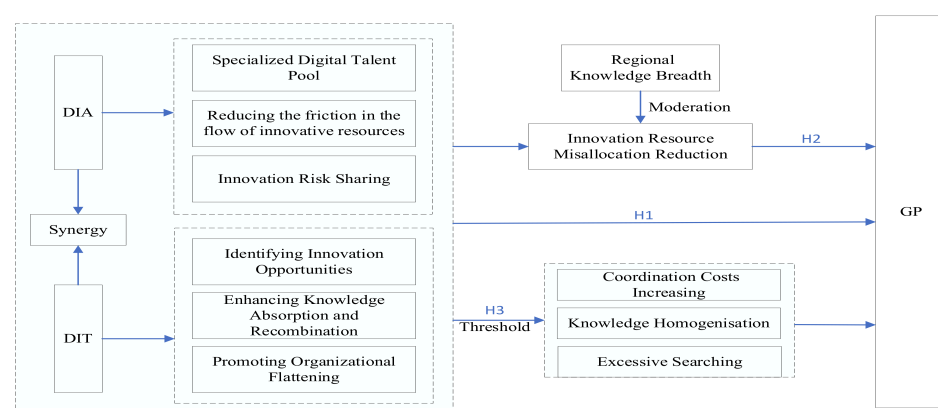


Figure 1. Theoretical Framework. Dashed boxes indicate theoretical mechanisms; arrows indicate the direction of influence.

H3. Once the DIA–DIT synergy level exceeds a certain threshold, its positive impact on GP forces diminishes.

4. Empirical Design

4.1. Simultaneous Equations Model

To validate the mutually reinforcing characteristics of DIA and DIT, and to explore their systemic features, a simultaneous equation model is formulated as follows:

$$\ln \text{dit}_{it} = \gamma_0 + \gamma_1 \ln \text{dia}_{it} + \gamma_2 X_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

$$\ln \text{dia}_{it} = \gamma_0 + \lambda_1 \ln \text{dit}_{it-1} + \gamma_2 X_{it} + \mu_i + \varepsilon_{it} \quad (2)$$

In this framework, $\ln \text{dia}_{it}$ denotes the DIA level of province i in year t , while $\ln \text{dit}_{it}$ indicates the DIT level in the same province and year. Considering the delayed response of DIT to DIA, a lag term $\ln \text{dit}_{it-1}$ is included in the model. Here, X_{it} acts as the control variable, μ_i represents the fixed effect, and ε_{it} is the random disturbance term. Estimation is performed using the three-stage least squares method, with the two-stage least squares method utilised to confirm the robustness of the results.

4.2. Multiple Regression Model

A panel regression model is utilised to examine the synergy effect of DIA and DIT on GP. The specifics are outlined below:

$$\text{Gp}_{it} = \alpha_0 + \alpha_1 \text{Sdd}_{it} + \alpha_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

In this context, Gp_{it} denotes the development level of GP, while Sdd_{it} signifies the level of DIA–DIT synergy. Additionally, X_{it} serves as the control variable, with μ_i and λ_t representing the individual and time fixed effects, respectively. Lastly, ε_{it} is the random disturbance term.

4.3. Moderated Mediation Model

This paper investigates how the DIA–DIT synergy affects GP indirectly by influencing the allocation of innovation resources. To analyse this, a moderated mediation model is utilised. Based on the research hypothesis and previous studies [54,55], the model is specified in Figure 2.

$$M_{it} = a_0 + a_1 \text{Sdd}_{it} + a_2 X_{it} + \varepsilon_{it} \quad (4)$$

$$\text{Gp}_{it} = b_0 + b_1 \text{Sdd}_{it} + b_2 M_{it} + b_3 W_{it} + b_4 W_{it} \times M_{it} + b_5 X_{it} + \varepsilon_{it} \quad (5)$$

$$\text{Cindirect}_{it} = \alpha_1 (b_2 + b_4 W_{it}) \quad (6)$$

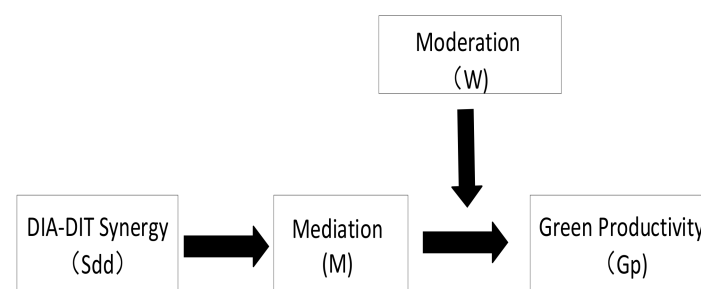


Figure 2. Moderated mediation effect. Arrows indicate the direction of influence.

Among these, $\ln m_{it}$ denotes the mediating variable: the degree of misallocation of innovation resources. Additionally, $\ln w_{it}$ moderates the relationship between the mediator and the explained variable; in this paper, it refers to the regional knowledge breadth level. $Cindirect_{it}$ denotes the conditional indirect effect, indicating that the moderator's value influences the magnitude of the indirect effect explained by the mediator. The conditional indirect effect is interpreted at specific values of the moderator.

4.4. Threshold Model

To further investigate the threshold effect of the DIA–DIT synergy on GP, a panel threshold model is constructed as follows:

$$Gp_{it} = \alpha_0 + \alpha_1 Sdd_{it} \times I(Adj_{it} \leq \theta) + \alpha_2 Sdd_{it} \times I(Adj_{it} > \theta) + \alpha_3 Sdd_{it} + \mu_i + \varepsilon_{it} \quad (7)$$

Among these variables, Adj_{it} serves as the threshold variable, indicating the level of DIA–DIT synergy. It also represents the level of DIA and regional knowledge breadth. $I(\cdot)$ denotes the indicator function.

4.5. Variable Selection

The synergy of digital industry agglomeration and the application of digital–intelligent technologies (DIA–DIT synergy). According to the theoretical definition of DIA–DIT synergy, it denotes an interdependent and mutually reinforcing interaction between DIA and DIT. The coupling–coordination model (CCM) is widely used to characterise such interdependent, reinforcing dynamics between two systems. Hence, this paper assesses the development levels of DIA and DIT separately and applies the coupling–coordination model (CCM) to quantify their synergistic effects.

The measurement of DIA. In accordance with the scope outlined in the Statistical Classification of the Digital Economy and Its Core Industries (2021) [56] by the National Bureau of Statistics of China, the digital product service industry and the digital product manufacturing industry are employed to represent the digital industry. The location quotient method is utilised for measurement, detailed as follows:

$$Dit_i = \frac{E_{ij} / \sum_j E_{ij}}{\sum_i E_{ij} / \sum_i \sum_j E_{ij}} \quad (8)$$

In this context, Dit_i denotes the level of DIA within region i . E_{ij} represents the number of employees in the digital industry service and manufacturing sectors in region i , while $\sum_j E_{ij}$ signifies the total number of employees in region i . Additionally $\sum_i E_{ij}$, refers to the number of employees in the national digital industry service and manufacturing sectors, and $\sum_i \sum_j E_{ij}$ indicates the total number of employees nationwide.

The measurement of DIT. This paper examines the level of DIT, with particular attention to digital and intelligent management and production at the micro-enterprise level. Building on existing research [57], we apply a text-analysis method to search for, match, and compute word-frequency statistics for DIT-related keywords in the annual reports of listed companies. DIT comprises two dimensions: digital and intelligent. The digital dimension centres on foundational information technologies, including data collection, management, analysis, trading, platforms and digital governance (The main word frequencies: data collection, data management, data integration, data modelling, data consolidation, data transaction data centre, digital platform, internet platform, cloud platform, data mining, data analysis, data visualisation, data-driven decision, data-driven, digital governance,

digital control, data warehouse, digital operation, digital manufacturing). The intelligent dimension emphasises advanced capabilities such as artificial intelligence, automation, robotics, intelligent systems and smart applications (The main word frequencies: intelligent operation, intelligent recommendation, intelligent system, smart management, smart production, smart device, smart workshop, smart manufacturing, industrial intelligence, smart factory, intelligent transportation, smart logistics, smart warehousing, smart distribution, smart energy, industrial internet, automated production, automatic control, automatic inspection, automatic monitoring, numerical control (NC), industrial robot). We then sum these frequencies and calculate the average to derive provincial-level DIT. Text analysis is justified as it captures firm-level digital engagement. To ensure the robustness of our findings and to avoid bias from the choice of specific text-based keywords, we use the number of internet access ports as an alternative proxy to validate this approach.

This paper utilises the Coupling Coordination Model (CCM) [58] to identify DIA–DIT synergy, which is detailed as follows:

$$T_{it}^2 = \alpha dia_{it} + \beta dit_{it} \quad (9)$$

Among these variables, dia_{it} and dit_{it} denote DIA and the enterprises' DIT, respectively. The notation α , β signifies the significance of both within the synergistic system. Subsequently, calculate the correlation between them:

$$C_{it}^2 = 2 \times \left[(dia_{it} \times dit_{it}) / \prod (dia_{it} + dit_{it}) \right]^{\frac{1}{2}} \quad (10)$$

The extent of DIA–DIT synergy can be articulated as

$$Sdd_{it} = \sqrt{C_{it}^2 \times T_{it}^2} \quad (11)$$

Green productivity (GP): GP represents a unique form of productivity that integrates traditional productivity attributes with green and sustainable principles. This paper defines GP as the optimisation of labour, means of labour, and objects of labour, with a significant enhancement in green total factor productivity as its main indicator. It represents an advanced form of productive forces aligned with contemporary development concepts. Consequently, drawing on relevant research [59], this study bases its analytical framework on the four fundamental elements of productive forces: green labourers, green means of labour, green objects of labour, and green performance, with a particular focus on scientific–technological advancement and eco-friendly manufacturing. Green objects of labour refer to the items processed and transformed during green production activities. The paper examines three dimensions: knowledge innovation, green ecology, and the energy environment. Green means of labour include the tools and knowledge capital used in green production, encompassing both tangible and intangible assets. Since environmental protection expenditures can be directly converted into tangible items like pollution-control facilities, this paper uses them to measure tangible assets. Green labourers are those capable of utilising green means of labour to act upon green objects of labour; they are evaluated based on labour quality, labour structure, and labour efficiency. Improvement in green performance is the main indicator of green productivity and is measured by the Green Total Factor Productivity Index (GTPF). A comprehensive assessment framework for green productivity is thereby established. Subsequently, the entropy-weighted method is utilised to thoroughly evaluate the development level of GP. The index system is detailed in Table 1.

Table 1. Index system of GP.

Normative Layer	Level 1 Indicators	Secondary Indicators	Measurement
Green Labourer	Labour quality	S&T personnel	R&D personnel full-time equivalent in above-scale industrial enterprises
	Labour structure	Human capital structure	Higher education enrollment/Total population
	Labour Productivity	GDP per capita	GDP/Total population
Green Object of Labour	Knowledge innovation	R&D output	Domestic patents granted
		Green innovation	Number of green patent applications
	Green ecology	Green expansion	Forest coverage rate
	Energy Environment	Energy utilisation	Energy consumption/GDP
		Reduce pollution	SO ₂ emissions per unit of GDP Industrial solid waste utilisation rate
Green Means of Labour	Tangible assets	Green tools	Proportion of environmental protection expenditure
	Intangible assets	R&D intensity	R&D expenditure intensity
Green performance	Green total factor productivity		GTFP index

Mediating variable. The measurement of regional knowledge breadth (Kb) is based on methodologies from existing studies [60,61]. Employing the concept of the Herfindahl–Hirschman Index (HHI), the concentration of regional technological field distribution is used to indicate regional knowledge breadth. A higher value of this indicator signifies a broader regional knowledge breadth, denoted as $\ln(kb) = \ln(1 - \sum \phi^2)$, where ϕ represents the share of a specific type of IPC number among all patents applied for in the region during that year.

The measurement of innovation resource allocation follows Klenow [62]. Internal R&D expenditure is used to estimate the innovation capital stock via the perpetual inventory method. The full-time equivalent of R&D personnel serves as a proxy for innovation human capital, and the number of granted patents is used as a measure of innovation output. The specific measurement is as follows:

Assume the production function follows a Cobb–Douglas form with constant returns to scale, specifically

$$Y_{it} = AK_{it}^{\beta_i} L_{it}^{1-\beta_i} \quad (12)$$

After logarithmic transformation, the results are as follows:

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = \ln A + \beta_{K_i} \ln\left(\frac{K_{it}}{L_{it}}\right) + \varepsilon_{it} \quad (13)$$

In this context, Y_{it} denotes the actual innovation output of province i in year t , while L_{it} signifies the innovation labour input of the same province and year. This study employs the full-time equivalent of R&D personnel for this measurement. Additionally, K_{it} represents the innovation capital input for province i in year t . The internal R&D expenditure is chosen for this purpose and is estimated via the perpetual inventory method, applying a standard capital depreciation rate of 9.6%.

A variable-coefficient panel regression model is used, with interaction terms between provincial dummies and the explanatory variables, to estimate province-specific capital-output elasticities, denoted as β_{K_i} . Assuming constant returns to scale, the labour-output

elasticity for each province is derived as $-1 - \beta_{K_i}$. Subsequently, the absolute distortion coefficient of factor prices is calculated as follows:

$$\gamma_{K_i} = \left(\frac{K_i}{K} \right) / \left(\frac{s_i \beta_{K_i}}{\beta_K} \right) \quad \gamma_{L_i} = \left(\frac{L_i}{L} \right) / \left(\frac{s_i \beta_{L_i}}{\beta_L} \right) \quad (14)$$

$$s_i = y_i / Y \quad \beta_K = \sum_i^N s_i \beta_{K_i} \quad (15)$$

Among them, s_i represents the share of innovation output of province i in the total output. β_K is the weighted contribution value of innovation capital. γ_{K_i} and γ_{L_i} denote the absolute price distortions of innovation capital and labour factors, respectively, which represent the degree to which the actual factor allocation level deviates from the optimal allocation. Accordingly, the misallocation indices for innovation capital and labour are computed as

$$\tau_{K_i} = \left| \frac{1}{\gamma_{K_i}} - 1 \right| \quad \tau_{L_i} = \left| \frac{1}{\gamma_{L_i}} - 1 \right| \quad (16)$$

The misallocation of innovation capital and personnel τ_{K_i} and τ_{L_i} denote the innovation capital misallocation index and the innovation labour misallocation index of province i , respectively. These indices indicate the extent to which the actual factor allocation deviates from the optimal allocation.

Control variables. We select control variables for economic development, human capital, and technological innovation that may influence GP. Economic development is captured by the degree of openness (Open) and tax level (Tax), measured, respectively, by the share of foreign investment and tax revenue in regional GDP. Human capital is reflected by the average years of schooling per capita (Edu). Technological innovation is gauged by the share of green invention patents and technology market turnover in GDP (Tech).

4.6. Data Sources

The data originates from the National Bureau of Statistics and the National Intellectual Property Administration, alongside statistical yearbooks including the China Statistical Yearbook, China Statistical Yearbook on Science and Technology, China Environmental Statistical Yearbook, and China Statistical Yearbook on Tertiary Industry. Where data were missing, a linear interpolation method was employed to fill the gaps. Owing to a significant lack of data in the Tibet Autonomous Region, this paper excludes data from that region.

5. Results

To test the foregoing theoretical hypotheses, the empirical results are presented as follows. Section 5.1 first defines the core variables and summarises their distributions. Section 5.2 then sets out the identification strategy, employing simultaneous equation and multiple-regression models to test Hypothesis 1. Section 5.3 investigates the mechanism through a moderated mediation model to evaluate Hypothesis 2. Section 5.4 assesses the nonlinear threshold using threshold regression to test Hypothesis 4. Finally, Section 5.5 reports robustness checks.

5.1. Descriptive Statistical Analysis

A descriptive analysis was conducted to characterise the distributions of the variables. As illustrated in Table 2 and Figure 3 the maximum value of DIA–DIT synergy is 0.959, while the minimum is 0.025. GP exhibits a similar pattern. These findings indicate significant inter-provincial variation in both DIA–DIT synergy and GP across China. Consequently,

several provinces have substantial potential for improvement, providing a valuable dataset for further analysis.

Table 2. Descriptive statistics results.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Dia	330	0.884	1.036	0.133	4.981
Dit	330	5.780	2.294	1.764	13.295
Sdd	330	0.410	0.178	0.025	0.959
Gp	330	0.282	0.159	0.027	0.740
τ_K	330	0.527	0.405	0.005	2.380
τ_L	330	0.201	0.168	0.002	0.897
τ_{KL}	330	0.370	0.237	0.031	1.456
Kb	330	0.966	0.010	0.888	0.977
Edu	330	9.441	0.901	7.514	12.681
Tech	330	0.022	0.033	0.000	0.195
Tax	330	0.079	0.029	0.035	0.200
Open	330	1.026	5.080	0.047	55.938

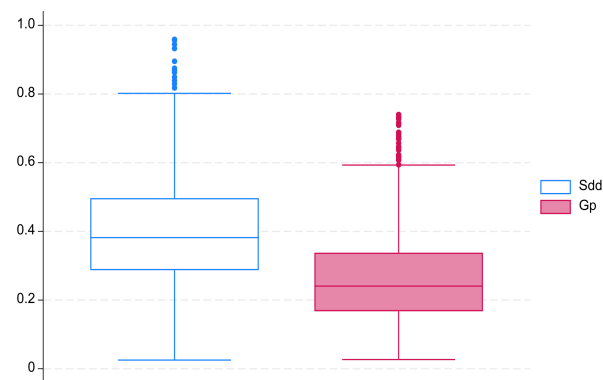


Figure 3. Box plot of Sdd and Gp. The left boxplot represents Sdd, and the right boxplot represents Gp. The box indicates the interquartile range (IQR), the line inside the box marks the median, and the whiskers extend to the minimum and maximum values within $1.5 \times \text{IQR}$.

Figure 4 illustrates the binned scatter plot of DIA–DIT synergy versus GP, after accounting for regional GDP weights. The fitted lowess curve reveals a consistently increasing and nearly linear trend, suggesting a positive association between DIA–DIT synergy and GP throughout the distribution.

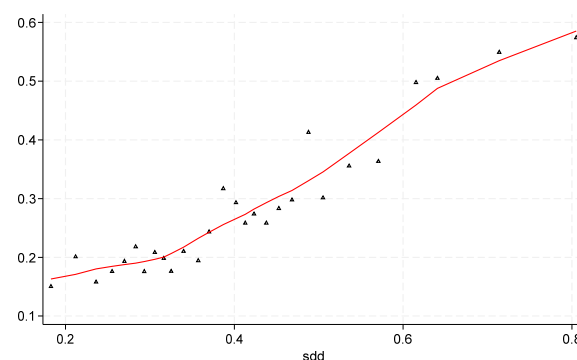


Figure 4. Trend plot of Sdd against Gp. Each dot represents the mean value of GP within equal-sized bins of Sdd; The solid line indicates the linear regression line fitted to the underlying data.

5.2. Benchmark Regression

As reported in columns (1)–(2) of Table 3, the simultaneous equations analysis reveals that, at the 5% significance level, DIA significantly enhances enterprises' DIT, with an estimated coefficient of 0.406. In turn, enterprises' DIT markedly boosts DIA, with a coefficient of 0.243. These results confirm the mutually reinforcing synergy between DIA and DIT, lending support to the theoretical framework of this study. The robustness of these findings is further supported by the two-stage least-squares estimations reported in columns (3) to (4) of Table 3, which yield consistent coefficients and significance levels.

Table 3. Simultaneous equation and multiple regression results.

	Lndit	Lndia	Lndit	Lndia	Gp
	(1)	(2)	(3)	(4)	(5)
	3SLS		2SLS		-
Sdd					0.230 *** (2.04)
Lndia	0.406 *** (2.60)		1.070 *** (3.29)		
Lndit _{it-1}		0.243 *** (6.15)		0.105 ** (1.96)	
Lndit					
Cons	−4.294 *** (−8.55)	0.446 (1.00)	−3.074 *** (−3.80)	−0.893 * (−1.79)	−1.568 *** (−2.76)
Num	330	330	330	330	330
R ²	0.659	0.152	0.663	0.113	0.675
Ctrl	Y	Y	Y	Y	Y
TFE	Y	Y	Y	Y	Y
PFE	Y	Y	Y	Y	Y

Note: “***”, “**”, and “*” indicate significance at the 1%, 5%, and 10% levels, respectively; TFE denotes time fixed effects; PFE denotes province fixed effects; Cons denotes the constant term. The same applies to the following tables, unless specified otherwise. Values in parentheses are t-statistics.

Further investigation was carried out to assess the impact of DIA–DIT synergy on GP. To account for potential omitted variables that remain constant over time and shared time trends across different provinces, a double fixed-effects model was employed for estimation. As shown in column (5) of Table 3, at a 5% significance level, DIA–DIT synergy significantly enhances GP, thereby confirming Hypothesis 1. These results reinforce the idea that digital transformation requires systemic alignment across organisational and environmental dimensions, consistent with the findings of Rangel Luzuriaga (2025) [63], who highlights the central role of digital competencies in enabling transformation outcomes in SMEs. Consequently, relevant departments can identify the optimal balance between DIA and DIT, tailored to regional development characteristics, to effectively boost GP.

5.3. Mechanism Analysis

To further elucidate the mechanism by which DIA–DIT synergy enhances GP, we turn to Table 4. Columns (1) and (2) reveal that DIA–DIT synergy significantly reduces the misallocation of innovation resources. Such misallocation adversely affects GP at the 5% level, with regional knowledge breadth mitigating this effect. Specifically, a wider regional knowledge breadth reduces the inhibitory impact of innovation resource misallo-

cation on GP. To assess the moderated mediation pathway, we evaluated the moderating variable at its mean and at ± 1 standard deviation and estimated the conditional indirect effect. From Columns (1) and (2) of the table, at the 5% significance level, the conditional indirect effect is stronger in the high knowledge breadth region, indicating that this effect persists where knowledge breadth is relatively large and thus partially corroborates the paper's conclusion. Similarly, columns (3) and (5) demonstrate that DIA–DIT synergy significantly diminishes the misallocation of innovation labour and capital at the 5% level. Further analysis in columns (4) and (6) indicates that both innovation labour and capital misallocation continue to significantly inhibit GP at the 5% level. Moreover, the conditional indirect effect test confirms that innovation labour misallocation mediates the relationship at the 5% significance level. Furthermore, the mediating effect of innovation capital misallocation is stronger in regions with high knowledge breadth, which further supports the moderated mediation pathway.

Table 4. Analysis of the moderated mediation effect.

	τ_{KL}	Gp	τ_L	Gp	τ_K	Gp
	(1)	(2)	(3)	(4)	(5)	(6)
Sdd	−0.634 *** (−3.61)	0.300 *** (2.66)	−1.246 (−7.75)	0.152 * (1.85)	−0.520 *** (−2.67)	0.147 * (1.85)
τ_{KL}		−2.561 ** (−2.01)				
$\tau_{KL} \times Kb$		2.695 *** (2.04)				
τ_L				−4.425 * (−1.70)		
$\tau_L \times Kb$				4.674 * (1.74)		
τ_K						−2.718 *** (−3.06)
$\tau_K \times Kb$						2.846 *** (3.10)
Cons	0.626 *** (4.77)	1.422 *** (5.35)	0.881 (7.33)	0.166 *** (3.37)	1.127 (0.41)	0.226 *** (4.82)
Num	330	330	330	330	330	330
Ctrl	Y	Y	Y	Y	Y	Y
TFE	Y	Y	Y	Y	Y	Y
PFE	Y	Y	Y	Y	Y	Y
n1_1(m − s)	−0.018		−0.080 **		−0.008	
n1_1(m)	−0.027 *		−0.111 ***		−0.016	
n1_1(m + s)	−0.036 **		−0.142 ***		−0.024 **	

Note: “***”, “**”, and “*” indicate significance at the 1%, 5%, and 10% levels, respectively. Values in parentheses are z-statistics.

Consequently, it is concluded that DIA–DIT synergy indirectly fosters GP by mitigating the misallocation of innovation resources. Hypothesis 2 is therefore supported. These findings suggest that the DIA–DIT synergy operates not only through scale effects but also through improved allocation of innovation resources, aligning with the resource orchestration and external enablement theories, which emphasise complementarities between external ecosystems and internal capabilities. This mechanism implies that reducing innovation resource misallocation is a key lever through which DIA–DIT synergy enhances GP. Therefore, to strengthen the positive impact of DIA–DIT synergy on GP, policies should

focus on fostering the co-evolution of DIA and DIT. This can be achieved by constructing a unified large market, lowering institutional barriers, and reducing cross-region mobility costs for skilled personnel and innovation resources.

5.4. Threshold Effects

We further examine the threshold characteristics of the DIA–DIT synergy in enhancing GP. Column (1) of Table 5 shows that, at the 5% significance level, the estimated threshold value is 0.635. Once the DIA–DIT synergy exceeds 0.635, the marginal cost of additional coordination outweighs its marginal benefit and yields diminishing returns. This implies an optimal synergy range beyond which further coordination becomes less effective, consistent with Hypothesis 4.

Table 5. Analysis of the threshold effect.

	(1)	(2)	(3)	(4)
Threshold Variable	Sdd	DIT	Ipc	Kb
Threshold θ	0.635 **	2.031 **	0.00 **	0.933 **
bootstrap P	0.016	0.020	0.013	0.050
$I(Sdd \times I(Adj \leq \theta))$	0.371 *** (4.29)	0.379 *** (4.46)	0.215 ** (2.35)	0.154 * (1.73)
$I(Sdd \times I(Adj > \theta))$	0.270 *** (3.24)	0.294 *** (3.57)	0.249 *** (2.71)	0.330 *** (3.73)
Cons	1.097 *** (4.58)	1.108 *** (4.68)	−3.274 *** (−8.74)	1.085 *** (3.83)
Ctrl	YES	Y	Y	Y
FE	Y	Y	Y	Y
Time	11	11	11	11
Province	30	30	30	30
Sigma-u	0.201	0.193	0.478	0.188
Sigma-e	0.046	0.045	0.073	0.048
Rho	0.950	0.948	0.977	0.939

Note: “***”, “**”, and “*” indicate significance at the 1%, 5%, and 10% levels, respectively. Values in parentheses are t-statistics.

To examine whether DIT itself imposes an additional threshold, we use the level of DIT application as the threshold variable. The results in Table 5, column 2, show that once DIT exceeds its threshold, the marginal contribution of the synergy to GP diminishes. A plausible economic interpretation is that excessive digitalisation can produce information overload and increase firms’ data-processing costs, thereby diverting attention away from core green-innovation activities. In other words, although a certain degree of DIT is required to unlock the synergy, excessive DIT can be counterproductive by raising managers’ cognitive burden and saturating the firm’s absorptive capacity; this aligns with the theoretical expectations of technology overload [64]. The finding accords with nonlinear relationships reported in earlier studies of digitalisation and productivity [65] and refines our understanding by showing that the synergy itself weakens at high DIT levels.

We next examine the threshold effect of innovation. Using the number of newly added IPC classes and regional knowledge breadth as threshold variables (Table 5, columns 3 and 4), we find that once these indicators exceed their respective thresholds, the impact of the DIA–DIT synergy on GP increases substantially. A narrow technological base induces geographical and cognitive lock-in, which traps firms in repetitive searches within the

same knowledge domain and thus diminishes the synergy's returns. Conversely, when IPC diversity and regional knowledge breadth cross the threshold, the innovation environment becomes technologically diversified and enables cross-domain recombination, thereby reducing redundant searches. Hence, the synergy's full potential is realised only in a sufficiently diverse and open innovation ecosystem, consistent with Goodman (2025) [66], who argues that institutions crucially affect patterns of recombination and innovation. For policymakers, these results imply that fostering technological diversity and preventing lock-in is as important as promoting digital-industrial synergy itself.

5.5. Robustness Test

5.5.1. Sensitivity to Omitted Variables

To assess the rationality of selecting control variables, the sensitivity analysis method proposed by Cinelli et al. (Cinelli et al., 2024) [67] is employed for the omitted variable test. Recognising human capital as a key driver of GP, the average years of schooling per capita is chosen as the comparison variable for the sensitivity analysis. Additionally, the technology market turnover in GDP is selected as another comparison variable to mitigate evaluation bias resulting from varying choices of comparison variables.

As illustrated in Figures 5 and 6, even in the worst-case scenario, omitted variables would need to be more than three times as influential as the average years of schooling per capita and the technology market turnover in GDP to overturn the previous conclusions. This indicates that the control variables selected in this paper are representative to a certain extent.

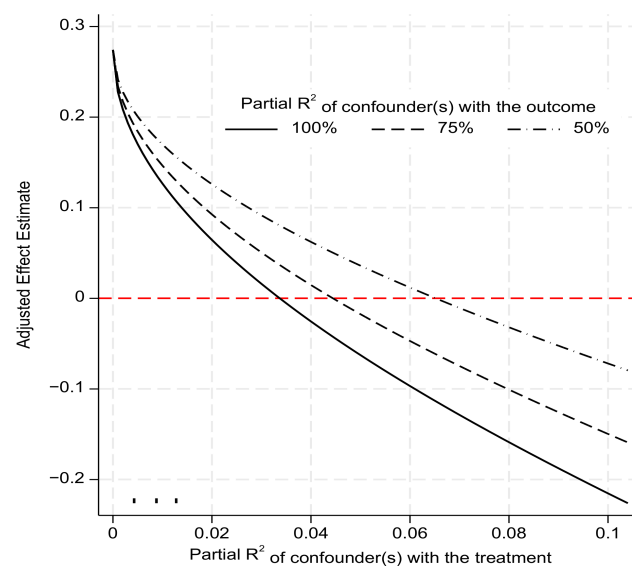


Figure 5. Robustness test of human capital. The black dots on the horizontal axis indicate the omitted-variable strength being 1 to 3 times that of human capital.

5.5.2. Endogeneity Test

Following the construction principles of Zhao et al. [35] and the Bartik instrumental variable, the interaction between regional terrain relief and lagged national Internet users is employed as the instrument. To strengthen its association with DIA–DIT synergy, the study squares this interaction and applies a logarithmic transformation. Topographic relief primarily impedes the development of DIA–DIT synergy by increasing the construction and maintenance costs of digital infrastructure, thus generating the observed correlation. As a naturally formed feature, topographic relief is exogenous and is unlikely to be affected by economic activity in the short term. Likewise, lagged national Internet users are not

influenced by the current regional economy, and thus satisfy the requirement of exogeneity. Regarding exclusivity, although the interaction between regional terrain undulations and lagging national Internet user numbers may correlate with other regional characteristics such as human capital and industrial structure, these characteristics do not provide an independent pathway influencing GP compared with DIA–DIT. Human capital affects GP primarily via its interaction with DIT [68]. The transformation of industrial structure in the digital era is itself driven by digitalisation [69], so its effect is encompassed by the DIA–DIT synergy. By contrast, environmental policies lack a direct causal link to terrain undulation and therefore satisfy the exclusivity requirement.

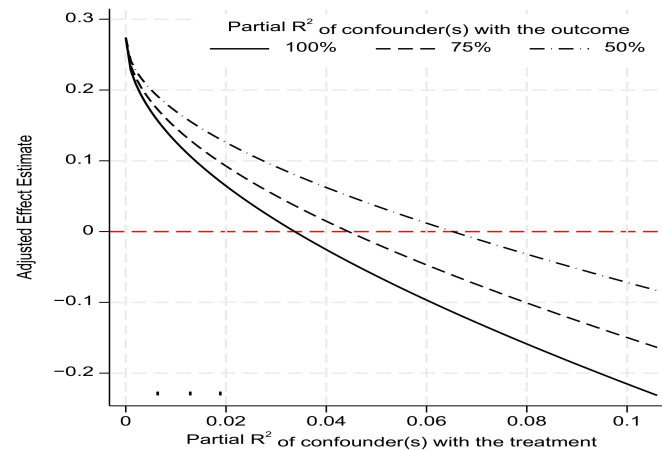


Figure 6. Robustness test of the technology. The black dots on the horizontal axis indicate the omitted-variable strength being 1 to 3 times that of technology.

The first-stage results in columns (1) and (2) of Table 6 indicate that the instrumental variable has a significant effect on the DIA–DIT synergy at the 5% level, confirming its relevance. The first-stage F-statistic exceeds 10, suggesting that the instrument is sufficiently strong and relevant. The LM test statistic is 11.722, which is significant at the 5% level and leads to rejection of the null of underidentification. The weak instrument CD test produces a value above the 15% critical threshold, indicating no weak-instrument problem. Thus, the instruments satisfy the relevance condition, and the exogeneity condition is conceptually justified, as discussed above. After adjusting for endogeneity, the positive effect of DIA–DIT synergy on GP remains significant at the 5% level, confirming the robustness of the finding.

Table 6. Robust test results.

	Endogeneity		Exclusivity		Spatial Effect	
	(1)	(2)	(3)	(4)	(5)	(6)
	First	2SLS	Area	Delete	Alternative	Main
Lng22	−0.003 *** (−3.46)					
Sdd	-	0.968 *** (2.04)	0.176 * (1.92)	0.260 *** (2.79)		0.274 *** (3.40)
Sdw					0.119 *** (2.76)	−0.326 * (−1.74)
Cons	-	-	−1.400 *** (−2.95)	−1.063 *** (−2.30)	−1.288 *** (−2.74)	
Rho						0.314 *** (3.70)

Table 6. Cont.

	Endogeneity		Exclusivity			Spatial Effect	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First	2SLS	Area	Delete	Alternative	Main	Spatial
Ctrl	Y	Y	Y	Y	Y	Y	Y
TFE	Y	Y	Y	Y	Y	Y	Y
PFE	Y	Y	Y	Y	Y	Y	Y
RFE	Y	N	Y	Y	Y	Y	Y
Endogeneity Test.	F test of excluded instruments					11.96 ***	
	Anderson LM statistic					11.722 ***	
	Cragg–Donald Wald F statistic				11.955 ***	15% maximal IV size 8.96	

Note: “***”, and “**” indicate significance at the 1%, and 10% levels, respectively. Values in parentheses are robust standard errors. RFE denotes regional fixed effects.

5.5.3. Exclusivity Test

This section examines the effects of regional factors, sample selection, and the choice of explanatory variables on the results. (1) Concerning regional factors, regional fixed effects are added alongside provincial fixed effects. A panel regression with cluster-robust standard errors at the provincial level is used to address potential bias from inter-provincial correlations and to mitigate the effects of macroeconomic instability. As shown in column (3) of Table 6, the positive effect of DIA–DIT synergy on GP remains statistically significant, confirming the earlier result. (2) At the sample level, due to the unique status of municipalities directly under the Central Government, data from Beijing, Tianjin, Shanghai, and Chongqing are excluded for re-estimation. Column (4) of Table 6 shows that the positive impact of DIA–DIT synergy on GP persists after removing these municipalities, supporting the generalisability of the conclusions. (3) To assess the choice of explanatory variable, the original variables are replaced with the number of internet access ports. As indicated in column (5) of Table 6, the results are consistent, which affirms the robustness of the study’s conclusions.

6. Further Analysis

To derive more comprehensive conclusions and provide supplementary analysis, we employ the spatial durbin model (SDM) to explore spatial effects in depth, particularly examining how the synergy between DIA and DIT influences GP through spatial spillovers. The SDM is specified as follows:

$$Gp_{it} = \lambda WGp_{it} + \gamma_1 Sdd_{it} + \gamma_2 X_{it} + WSdd_{it}\delta + c_i + \gamma_t + \mu_{it} \quad (17)$$

This paper examines spatial interaction between adjacent regions and therefore adopts the adjacency matrix W as the spatial weight matrix. For robustness, the geographical distance matrix W_2 is also employed to verify the conclusions. The spatial weight matrix W is specified as follows: $W_2 = \begin{cases} 0 & i = j \\ \frac{1}{d_{ij}^2} & i \neq j \end{cases}$ Here, d_{ij} signifies the geographical distance between province i and province j , measured using longitude and latitude. Additionally, X_{it} serves as the control variable, c_i denotes the individual effect, γ_t represents the time effect, and μ_{it} is the spatial lag error term.

According to Table 7, the Lagrange multiplier (LM) test results indicate that both the spatial error model (SEM) and the spatial lag model (SAR) are significant at the 1% level.

The robust LM tests yield the same conclusion, confirming the presence of spatial effects and suggesting that the spatial Durbin model (SDM), which accounts for both dependent and independent variable spatial correlations, is more appropriate. The Hausman test statistic is negative, which in finite samples can result from the variance–covariance matrix of the difference between the fixed-effect and random-effect estimators not being positive definite. Given that inter-provincial development disparities can produce time-invariant omitted variables, and that neglecting provincial heterogeneity and temporal effects may bias the results, this paper therefore employs a two-way fixed-effect spatial Durbin model for spatial regression.

Table 7. Test for spatial effects.

	Test	Statistic	<i>p</i>
LM Test	LM-error	55.085	0.000 ***
	RLM-error	55.509	0.000 **
	LM-lag	4.723	0.033 **
	RLM-lag	5.147	0.023 **
Hausman Test	Chi2(9)	−180.23	-
Wald Test	SAR	35.23	0.000 ***
	SEM	36.55	0.000 ***
Effect Selection	Ind-Both	66	0.000 ***
	Time-Both	409.19	0.000 ***

Note: “****” and “***” indicate significance at the 1% and 5% levels, respectively.

Columns (1)–(2) of Table 8 indicate that at the 5% significance level, the direct effect coefficient of DIA–DIT synergy on GP is 0.172. Meanwhile, the spatial effect coefficient is −0.298, significant at the 10% level. This suggests that while DIA–DIT synergy boosts local green productivity, it has a negative spatial spillover effect. In other words, increased DIA–DIT synergy in neighbouring areas appears to hinder local green productivity, possibly due to a syphon effect that diverts resources from surrounding regions.

If this mechanism is valid, the syphon effect should be more pronounced in regions with high economic development and weaker or absent in less developed areas. To test this hypothesis, the paper introduces a moderating variable representing the stage of economic development to explore variations in spatial effects across different development stages. The industrial structure is quantified by the ratio of the tertiary industry’s output value to that of the secondary industry in each region; a higher ratio indicates a more advanced development stage. The sample is then divided into underdeveloped and developed groups based on the median of this ratio, which acts as a proxy for the development stage. As indicated in columns (3)–(4) of Table 8, after incorporating the moderating variable, the spatial effect coefficient of DIA–DIT synergy on GP is 0.465 at the 5% significance level, while the spatial moderation coefficient is −0.465 (both significant and negative). This suggests that during the underdeveloped stage, DIA–DIT synergy generates positive spatial spillovers for GP, whereas in the developed stage, the syphon effect and increased competition lead to negative spillovers in neighbouring areas.

Given the spatial regression model’s sensitivity to the spatial matrix, we employed the geographical distance matrix for additional regression to test the robustness of our conclusions. The detailed results are presented in columns (6)–(7) of Table 6, and they align with our initial findings. Consequently, the conclusions of this paper demonstrate considerable robustness.

Table 8. Analysis of the spatial effects.

	Synergy		Moderation		Effect Decomposition		
	Main	Spatial	Main	Spatial	Direct	Indirect	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sdd	0.172 ** (2.13)	−0.298 * (−1.84)	0.423 *** (4.89)	0.465 ** (2.50)	0.446 *** (4.96)	0.608 *** (2.79)	1.055 *** (4.17)
Me15			0.053 * (1.78)	0.208 ** (4.30)	0.061 *** (2.16)	0.249 *** (4.67)	0.310 *** (5.92)
Sdd × Me15			−0.171 ** (−2.32)	−0.465 ** (−4.13)	−0.186 *** (−2.65)	−0.560 *** (−4.50)	−0.746 *** (−6.18)
rho		0.172 ** (2.34)		0.155 ** (2.12)			
Ctrl	Y	Y	Y	Y	Y	Y	Y
PFE	Y	Y	Y	Y	Y	Y	Y
TFE	Y	Y	Y	Y	Y	Y	Y
Num	330	330	330	330	330	330	330
R2	0.296		0.472				0.17

Note: “***”, “**”, and “*” indicate significance at the 1%, 5%, and 10% levels, respectively.

7. Conclusions

This study integrates external enablement theory and resource orchestration theory to propose a unified External Enablement–Resource Orchestration (EERO) framework. Within this framework, DIA–DIT synergy is conceptualised as a mutually reinforcing process wherein DIA provides external resource structuring, and DIT enables internal resource bundling and leveraging. Moreover, we revisit green productivity through the three fundamental elements of productive forces: labourers, means of labour, and objects of labour, thereby enriching the research content on green productivity.

Using provincial panel data from 2013 to 2023, we construct a simultaneous equation model to examine the joint system by which DIA and DIT co-evolve and jointly enhance green productivity (GP). We also employ a moderated mediation model to identify innovation–resource misallocation as the mediating pathway through which DIA–DIT synergy influences GP. This finding is consistent with predictions from resource orchestration theory and suggests its potential extension to the green transition context. Finally, we apply threshold and spatial econometric models to explore the nonlinear dynamics and spatial spillover effects of this synergy on GP.

The main findings are as follows:

1. DIA and DIT are found to exhibit synergistic and cumulative effects that collectively enhance GP. Mechanism analysis suggests that reducing innovation resource misallocation, particularly in R&D capital, serves as a mediating pathway through which these factors influence GP. Furthermore, regional knowledge breadth is found to mitigate the impact of this misallocation on GP.
2. Once the level of DIA–DIT synergy exceeds a specific threshold, its influence on GP tends to diminish. Conversely, when the activity within the regional knowledge breadth exceeds this threshold, this positive impact on GP is amplified, which is consistent with the proposed nonlinear expectation.
3. The **synergistic** development of DIA and DIT generates positive spatial spillovers for GP. The spatial spillover of this synergy on GP depends on the stage of development: in less developed regions, the DIA–DIT synergy generates a positive spillover

for GP, whereas in developed regions it tends to generate a negative spillover for neighbouring areas.

Based on our findings, several policy implications for economies pursuing digital-driven productivity growth are as follows:

4. To strengthen the intermediary pathway and consolidate the foundation for collaborative development, governments can lower enterprises' adoption costs for digital-intelligent technologies through R&D subsidies and similar instruments. Leveraging these technologies, the development of a cross-regional R&D capital supply–demand platform can be promoted to channel innovation resources toward enterprises within digital industrial clusters. Regularly facilitating knowledge-sharing events such as digital industry innovation forums can further enhance knowledge flow and collaboration within the cluster.
5. To unlock the advanced drivers of coordinated development, policies must address threshold constraints. In regions below the synergy threshold, initial efforts should prioritise strengthening digital infrastructure and upgrading traditional industries through digitalisation to enhance DIA–DIT synergy. For regions above the threshold, the focus should shift to fostering deep, innovative integration of digital-intelligent technologies and vigorously advancing mission-oriented initiatives such as “Artificial Intelligence+”. At the same time, policy incentives should be designed to encourage firms' digital and intelligent transformation, while optimising the technology market and industrial environment to lower matching costs between technology suppliers and adopters.
6. To amplify spatial spillovers and extend the reach of synergistic development, policies can support the digital industry's shift from geographical concentration toward networked clusters. Leveraging technologies such as cloud computing and big data, national or cross-regional digital platforms can be fostered to facilitate the flow of technology, data, and talent across regions.
7. Strategic use of regional disparities is also essential. A cooperation framework can be developed to support cross-regional industrial transfer and collaborative R&D, enabling the diffusion of digital-intelligent technologies from advanced to neighbouring regions. Simultaneously, less-developed areas should strengthen their knowledge absorption capacity through targeted talent programmes and infrastructure improvements.

8. Limitations and Future Research

This study provides new insights into research on digitally enabled green productivity. However, the findings are limited to Chinese provincial data, which may restrict their generalizability to other institutional settings or to the micro-level of individual firms. Furthermore, although we identify a moderating role of regional knowledge breadth, the underlying institutional and cultural mechanisms remain to be further unpacked. Accordingly, future research could explore how different institutional environments and cultural factors influence the intensity and direction of DIA–DIT synergy, particularly in contexts where digital infrastructure and governance mechanisms are still evolving.

Author Contributions: Methodology, S.L.; software, S.L.; validation, S.L.; resources, H.H.; data curation, S.L.; writing—original draft preparation, S.L.; supervision, H.H.; funding acquisition, H.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Social Science Found of China, grant number 25BTJ028.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding authors.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Fu, J.; Liu, Y.; Jiang, L. Artificial Intelligence Technology Application and Corporate Green Productivity: A Study on Financial Transmission Mechanisms. *Finance Res. Lett.* **2026**, *101*, 109936. [\[CrossRef\]](#)
2. Scholtysik, M.; Rasor, A.; Petzke, L.; Koldewey, C.; Dumitrescu, R. An integrative perspective on digital technologies and circular economy: A systematic literature review. *Proc. Des. Soc.* **2025**, *5*, 541–550. [\[CrossRef\]](#)
3. World Bank. *Digital Progress and Trends Report 2025: Strengthening AI Foundations*; World Bank: Washington, DC, USA, 2025.
4. Andrews, D.; Nicoletti, G.; Timiliotis, C. *Digital Technology Diffusion: A Matter of Capabilities, Incentives or Both?* OECD: Paris, France, 2018.
5. Organisation for Economic Co-Operation and Development. *Digitalisation and Productivity: A Story of Complementarities*; Organisation for Economic Co-Operation and Development: Paris, France, 2021.
6. Hunjra, A.I.; Zhao, S.; Tan, Y.; Bouri, E.; Liu, X. How do green innovations promote regional green total factor productivity? Multidimensional analysis of heterogeneity, spatiality and nonlinearity. *J. Clean. Prod.* **2024**, *467*, 142935. [\[CrossRef\]](#)
7. Wang, J.; Guo, D. Siphon and radiation effects of ICT agglomeration on green total factor productivity: Evidence from a spatial Durbin model. *Energy Econ.* **2023**, *126*, 106953. [\[CrossRef\]](#)
8. Yi, L.; Zhang, W.; Ding, Y. Cloud Computing and Green Total Factor Productivity in Urban China: Evidence from a Spatial Difference-in-Differences Approach. *Sustainability* **2025**, *17*, 9828.
9. Yang, S.; Chen, Y.; Chen, H.; Ye, B.; Shao, S. Digital enterprise distribution and green total factor productivity: A spatial agglomeration perspective. *Environ. Impact Assess. Rev.* **2025**, *112*, 107832. [\[CrossRef\]](#)
10. Fazio, G.; Maioli, S.; Rujimora, N. The twin innovation transitions of European regions. *Reg. Stud.* **2025**, *59*, 2309176.
11. Sergio, I.; Iandolo, S.; Ferragina, A.M. Inter-sectoral and inter-regional knowledge spillovers: The role of ICT and technological branching on innovation in high-tech sectors. *Technol. Forecast. Soc. Change* **2023**, *194*, 122728.
12. Lei, X.; Shen, Z.; Štreimikienė, D.; Baležentis, T.; Wang, G.; Mu, Y. Digitalization and sustainable development: Evidence from OECD countries. *Appl. Energy* **2024**, *357*, 122480.
13. Wang, J.; Qiao, L.; Zhu, G.; Di, K.; Zhang, X. Research on the driving factors and impact mechanisms of green new quality productive forces in high-tech retail enterprises under China's Dual Carbon Goals. *J. Retail. Consum. Serv.* **2025**, *82*, 104092. [\[CrossRef\]](#)
14. Brynjolfsson, E.; Hitt, L.M. Beyond Computation: Information Technology, Organizational Transformation and Business Performance. *J. Econ. Perspect.* **2000**, *14*, 23–48. [\[CrossRef\]](#)
15. Bharadwaj, A.; El Sawy, O.A.; Pavlou, P.A.; Venkatraman, N. Digital Business Strategy: Toward a Next Generation of Insights. *MIS Q.* **2013**, *37*, 471–482. [\[CrossRef\]](#)
16. Han, Y.; Li, Z.; Feng, T.; Qiu, S.; Hu, J.; Yadav, K.K.; Obaidullah, A.J. Unraveling the impact of digital transformation on green innovation through microdata and machine learning. *J. Environ. Manag.* **2024**, *354*, 120271. [\[CrossRef\]](#)
17. Wu, Q.; Li, S. Decarbonization by digits: How data factors drive nonlinear sustainable dynamics in manufacturing. *Appl. Energy* **2024**, *374*, 123967. [\[CrossRef\]](#)
18. Yuan, B.; Chen, K. Cautionary perspectives on greenhouse impact of innovation: Exploring the nonlinear link between breakthrough low-carbon technological innovation and corporate carbon emissions. *J. Innov. Knowl.* **2026**, *16*, 101030. [\[CrossRef\]](#)
19. Chen, Y.; Huang, X.; Liu, C. Can AI computing power promote the green transformation of energy enterprises? Evidence from the nonlinear moderating effect of public environmental awareness. *J. Environ. Manag.* **2025**, *391*, 126455. [\[CrossRef\]](#)
20. Xu, M.; Tan, R. Digital economy as a catalyst for low-carbon transformation in China: New analytical insights. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 841. [\[CrossRef\]](#)
21. Lee, M.-J.; Kim, Y.; Roh, T. Exploring the role of digital servitization for green innovation: Absorptive capacity, transformative capacity, and environmental strategy. *Technol. Forecast. Soc. Change* **2024**, *207*, 123614. [\[CrossRef\]](#)
22. Lu, S.; Liu, J.; Wang, X.; Zhang, W. Absorptive capacity and the low-carbon impact of external digital and green technologies. *Technol. Soc.* **2025**, *84*, 103123. [\[CrossRef\]](#)
23. Li, L.; Zeng, Y.; Xia, D. How Does the Digital Innovation Ecosystem Enable Green Regional Development? A Dynamic QCA Study in China. *Systems* **2024**, *12*, 551. [\[CrossRef\]](#)

24. Lu, K.; Qiu, Y.; Zhang, J.; Li, C.; Xie, J. Digital industry agglomeration and inclusive green growth: Synergies and path exploration. *Front. Environ. Sci.* **2025**, *13*, 1552159. [[CrossRef](#)]
25. Vásquez, Ó.; Sandulli, F.D.; Gallego, J. Technological agglomerations and the emergence of artificial intelligence start-up ecosystems in Europe. *Technol. Soc.* **2025**, *84*, 103092. [[CrossRef](#)]
26. Chen, X.; Chen, Y.; Huang, W.; Zhang, X. A new Malmquist-type green total factor productivity measure: An application to China. *Energy Econ.* **2023**, *117*, 106408.
27. Li, T.; Ormeño-Candelario, V.; Chen, X. Assessing agricultural green total factor productivity in Latin America. *Agribusiness* **2024**, *42*, 784–797. [[CrossRef](#)]
28. Zaman, A.U.; Valiyattoor, V. Evaluating the green total factor productivity and convergence among emerging and resource intensive economies. *Discov. Sustain.* **2025**, *6*, 1053. [[CrossRef](#)]
29. Teng, Y.; Zheng, J.; Li, Y.; Wu, D. Optimizing digital transformation paths for industrial clusters: Insights from a simulation. *Technol. Forecast. Soc. Change* **2024**, *200*, 123170. [[CrossRef](#)]
30. Zhan, J.; Wang, X.; Li, Q.; Zhao, J. Digital Industry Agglomeration and Export Product Diversification: Evidence from Chinese Firms. *China World Econ.* **2025**, *33*, 64–100. [[CrossRef](#)]
31. Kuang, A.; Yeung, G.; Wang, M.; Tong, Y. Digital Platform, Spatial-Digital Fix, and the Reconfiguration of Apparel Production Networks. *Econ. Geogr.* **2024**, *100*, 381–409. [[CrossRef](#)]
32. Moriset, B.; Malecki, E.J. Organization versus space: The paradoxical geographies of the digital economy. *Geogr. Compass* **2009**, *3*, 256–274. [[CrossRef](#)]
33. Davidsson, P. Entrepreneurial opportunities and the entrepreneurship nexus: A re-conceptualization. *J. Bus. Ventur.* **2015**, *30*, 674–695. [[CrossRef](#)]
34. Sirmon, D.G.; Hitt, M.A.; Ireland, R.D. Managing firm resources in dynamic environments to create value: Looking inside the black box. *Acad. Manag. Rev.* **2007**, *32*, 273–292. [[CrossRef](#)]
35. Zhao, H.; Cao, X.; Ma, T. Digital industrial agglomeration and breakthrough technological innovation: Evidence from business registration data. *Technol. Soc.* **2026**, *85*, 103161. [[CrossRef](#)]
36. Lu, D.; Hui, E.C.M.; Shen, J.; Shi, J. Digital industry agglomeration and urban innovation: Evidence from China. *Econ. Anal. Policy* **2024**, *84*, 1998–2025. [[CrossRef](#)]
37. Strange, W.; Hejazi, W.; Tang, J. The uncertain city: Competitive instability, skills, innovation and the strategy of agglomeration. *J. Urban Econ.* **2006**, *59*, 331–351. [[CrossRef](#)]
38. Wang, Z.; Liu, H. Can intelligent transformation enhance corporate green innovation performance? *Finance Res. Lett.* **2025**, *81*, 107426. [[CrossRef](#)]
39. Brynjolfsson, E.; Rock, D.; Syverson, C. The productivity J-curve: How intangibles complement general purpose technologies. *Am. Econ. J. Macroecon.* **2021**, *13*, 333–372. [[CrossRef](#)]
40. Xing, X.; Chen, T.; Yang, X.; Liu, T. Digital transformation and innovation performance of China's manufacturers? A configurational approach. *Technol. Soc.* **2023**, *75*, 102356. [[CrossRef](#)]
41. Chen, H.; Chiang, R.H.; Storey, V.C. Business intelligence and analytics: From big data to big impact. *MIS Q.* **2012**, *36*, 1165–1188. [[CrossRef](#)]
42. Urbinati, A.; Chiaroni, D.; Chiesa, V.; Frattini, F. The role of digital technologies in open innovation processes: An exploratory multiple case study analysis. *RD Manag.* **2020**, *50*, 136–160.
43. Gao, Y.; Liu, S.; Yang, L. Artificial intelligence and innovation capability: A dynamic capabilities perspective. *Int. Rev. Econ. Finance* **2025**, *98*, 103923. [[CrossRef](#)]
44. Colfer, L.J.; Baldwin, C.Y. The mirroring hypothesis: Theory, evidence, and exceptions. *Ind. Corp. Change* **2016**, *25*, 709–738. [[CrossRef](#)]
45. Milgrom, P.; Roberts, J. Complementarities and fit strategy, structure, and organizational change in manufacturing. *J. Account. Econ.* **1995**, *19*, 179–208. [[CrossRef](#)]
46. March, J.G. Exploration and exploitation in organizational learning. *Organ. Sci.* **1991**, *2*, 71–87. [[CrossRef](#)]
47. Bathelt, H.; Malmberg, A.; Maskell, P. Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. *Prog. Hum. Geogr.* **2004**, *28*, 31–56. [[CrossRef](#)]
48. Baqaee, D.R.; Farhi, E. Productivity and misallocation in general equilibrium. *Q. J. Econ.* **2020**, *135*, 105–163.
49. Balland, P.-A.; Belso-Martínez, J.A.; Morrison, A. The dynamics of technical and business knowledge networks in industrial clusters: Embeddedness, status, or proximity? *Econ. Geogr.* **2016**, *92*, 35–60.
50. Bercovitz, J.; Feldman, M. The mechanisms of collaboration in inventive teams: Composition, social networks, and geography. *Res. Policy* **2011**, *40*, 81–93. [[CrossRef](#)]
51. Beaudry, C.; Schiffauerova, A. Who's right, Marshall or Jacobs? The localization versus urbanization debate. *Res. Policy* **2009**, *38*, 318–337.
52. Boschma, R. Proximity and innovation: A critical assessment. *Reg. Stud.* **2005**, *39*, 61–74. [[CrossRef](#)]

53. Laursen, K.; Salter, A. Open for innovation: The role of openness in explaining innovation performance among UK manufacturing firms. *Strateg. Manag. J.* **2006**, *27*, 131–150.
54. Hayes, A.F. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*; Guilford Publications: New York, NY, USA, 2017.
55. Preacher, K.J.; Rucker, D.D.; Hayes, A.F. Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivar. Behav. Res.* **2007**, *42*, 185–227. [[CrossRef](#)]
56. GB/T 4754; Statistical Classification of the Digital Economy and Its Core Industries. National Bureau of Statistics of China: Beijing, China, 2021.
57. Zou, X.; Fu, Z.; Tian, Z.; Peng, Z. Can the application of artificial intelligence technology and financial innovation drive the digital transformation of enterprises? *Int. Rev. Financ. Anal.* **2025**, *109*, 104758. [[CrossRef](#)]
58. Li, M.; Wang, Z.; Wei, Z. Digital new quality productivity and high-quality development of enterprises. *Int. Rev. Financ. Anal.* **2025**, *109*, 104811. [[CrossRef](#)]
59. Cui, X.; Yu, C.; Zhou, J. Does agricultural insurance promote the new-quality productivity? Evidence from double machine learning. *Int. Rev. Econ. Finance* **2025**, *105*, 104797. [[CrossRef](#)]
60. Akcigit, U.; Baslandze, S.; Stantcheva, S. Taxation and the International Mobility of Inventors. *Am. Econ. Rev.* **2015**, *106*, 2930–2981.
61. Jie, Z.; Wenping, Z. Has Catch-Up Strategy of Innovation Inhibited the Quality of China's Patents? *Econ. Res. J.* **2018**, *53*, 28–41.
62. Klenow, H.P.J. Misallocation and Manufacturing TFP in China and India. *Q. J. Econ.* **2009**, *124*, 1403–1448. [[CrossRef](#)]
63. Luzuriaga, E.W.R. A Moderated Model of Digital Transformation in SMEs: Digital Competencies, Digital HRM, and Organizational Culture. *Ceniiac* **2025**, *1*, e0010. [[CrossRef](#)]
64. Karr-Wisniewski, P.; Lu, Y. When more is too much: Operationalizing technology overload and exploring its impact on knowledge worker productivity. *Comput. Hum. Behav.* **2010**, *26*, 1061–1072. [[CrossRef](#)]
65. Suo, X.; Zhang, L.; Guo, R.; Lin, H.; Yu, M.; Du, X. The inverted U-shaped association between digital economy and corporate total factor productivity: A knowledge-based perspective. *Technol. Forecast. Soc. Change* **2024**, *203*, 123364.
66. Goodman, N.P.; Lehto, O.; Novak, M. Institutional diversity and innovative recombination. *Eur. Econ. Rev.* **2025**, *174*, 104998. [[CrossRef](#)]
67. Cinelli, C.; Ferwerda, J.; Hazlett, C. Sensemakr: Sensitivity Analysis Tools for OLS in R and Stata. *Obs. Stud.* **2024**, *10*, 93–127. [[CrossRef](#)]
68. Chen, H.; Yu, Z.; Hu, S. Digital economy, human capital accumulation, and corporate green total factor productivity: Based on strategic emerging industries. *Int. Rev. Financ. Anal.* **2025**, *103*, 104152. [[CrossRef](#)]
69. Chang, H.; Ding, Q.; Zhao, W.; Hou, N.; Liu, W. The digital economy, industrial structure upgrading, and carbon emission intensity—Empirical evidence from China's provinces. *Energy Strategy Rev.* **2023**, *50*, 101218.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.