

Study on the Spatial Effects and Micro-Level Transmission Mechanisms of Digital Economy Empowering Innovation Performance in Manufacturing

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Abstract

The deep integration of the digital economy and the manufacturing sector constitutes a critical pathway for fostering industrial innovation and high-quality development. Utilizing panel data from 11 provinces within the Yangtze River Economic Belt (2015–2023), this study employs the Spatial Durbin Model (SDM) and Structural Equation Modeling (SEM) to investigate the transmission mechanisms and spatial spillover effects of the digital economy on manufacturing innovation performance. The findings indicate that: (1) The digital economy acts as a significant driver of manufacturing innovation performance, with a total effect coefficient of 1.327. The decomposition of this impact—61.8% direct and 38.2% indirect—highlights a dual-drive characteristic involving both technological empowerment and institutional optimization. (2) The innovation-promoting effect exhibits spatial correlation; specifically, while the digital economy exerts a slight direct inhibitory effect locally, it generates significant positive spatial spillovers to neighboring regions, suggesting a potential "siphon effect" arising from inter-regional factor competition. (3) The transmission pathways display significant threshold characteristics. The mediating mechanisms are fully activated only after the digital economy surpasses a specific developmental threshold, implying that the empowerment effect is contingent upon the maturity of the digital ecosystem. This study provides theoretical foundations and policy insights for implementing differentiated digital development strategies, constructing cross-regional innovation collaborative systems, and advancing the deep fusion of digital technology and manufacturing.

Keywords

Digital Economy; Innovation Performance; Structural Equation Modeling (SEM); Spatial Durbin Model (SDM).

1. Literature Review and Hypothesis Presentation

1.1. Literature Review

With the rapid advancement of information technology, the digital economy has emerged as a new engine propelling global economic development. Its core characteristic lies in data becoming a key factor of production, restructuring production relations and resource allocation through the deep integration of digital technologies and the real economy (Hong Yinxing et al., 2023)^[1]. Based on micro-enterprise data, Dai Xiang et al. (2022)^[2] confirmed that digital empowerment facilitates manufacturing transformation through scale effects and technological effects, while generating industrial linkage spillover effects. Furthermore, Shi Bo et al. (2024)^[3] differentiated digital transformation into technology-driven and application-driven modes, revealing the heterogeneous pathways through which digital technologies operate.

At the regional level, the spatial attributes of the digital economy significantly condition its efficacy. Zhou Yuanren et al. (2025)^[4], utilizing provincial data, identified a "High-East, Low-West" gradient distribution in China's digital economy, characterized by geographical agglomeration and disequilibrium in the spatial correlation network. Treating industrial internet pilots as a natural experiment, Chao Xiaojing et al. (2024)^[5] verified that such initiatives significantly enhance total factor productivity (TFP) in manufacturing through resource integration and supply chain efficiency improvements, thereby highlighting the critical role of digital infrastructure.

The enhancement of manufacturing innovation performance is driven by multiple factors. Adopting a digital innovation network perspective, Yang Zhenning et al. (2025)^[6] found that network embedding significantly promotes corporate innovation in key core technologies by facilitating knowledge boundary spanning. Tang Yaojia et al. (2022)^[7] proposed that the impact of the digital economy on innovation performance exhibits dynamic non-linear characteristics, evolving through stages of "innovation potential latency," "innovation integration release," and "innovation performance constraint." Spatially, Dou Jianmin et al. (2023)^[8] utilized urban data to confirm significant positive spatial spillovers of the digital economy on collaborative innovation. Conversely, Bo Wenguang et al. (2025) pointed out the possibility of negative spatial spillovers, reflecting inter-regional resource competition.

The nexus between the digital economy and manufacturing innovation performance demonstrates multi-pathway characteristics. Liu Shuchun et al. (2021) observed that the output elasticity of capital in digital management far exceeds that of labor, and the relationship between digital investment and efficiency follows a "U-shaped" pattern (declining first, then rising), indicating that resource allocation efficiency is a pivotal mediator. Zhang Guosheng et al. (2022) noted that digital transformation tends to promote the "quantity" of technological innovation while inhibiting its "quality," revealing a divergence mechanism between innovation volume and substance.

Despite the rich findings of existing literature, three limitations remain: First, systematic empirical evidence on micro-transmission mechanisms, such as resource allocation efficiency, is relatively scarce. Second, there is divergence regarding the direction and scope of spatial spillovers, with most studies relying on single spatial weight matrices. Third, research on the contingent conditions for non-linear relationships is insufficient, failing to provide precise bases for differentiated policies.

Building on a theoretical framework, this study comprehensively employs the Spatial Durbin Model (SDM), Structural Equation Modeling (SEM), Panel Threshold Regression, and System GMM methods. It systematically explores the spatial effects and micro-transmission paths of the digital economy on manufacturing innovation performance. This research aims to bridge existing gaps and provide theoretical support and policy references for regional coordination and micro-optimization of manufacturing innovation in the context of the digital economy.

1.2. Theoretical Analysis

The digital economy, characterized by data resources as a key factor of production and the deep integration of information and communication technology (ICT) with the real economy (Statistical Classification of the Digital Economy and Its Core Industries, 2021), offers new theoretical space for explaining manufacturing innovation. This paper constructs an analytical framework by synthesizing Regional Innovation System (RIS) Theory and Dynamic Capabilities (DC) Theory.

RIS theory emphasizes the spatial embeddedness and network interactivity of innovation activities, positing that the regional institutional environment, knowledge infrastructure, and industrial collaborative networks constitute critical pillars of the innovation system. Conversely, DC theory focuses on an enterprise's capacity to sense, learn, integrate, and

reconfigure in response to the external environment, highlighting the core mechanisms for maintaining competitive advantage amidst dynamic changes. The integration of these two theories provides a dual perspective of "Macro-System Support - Micro-Capability Response" for understanding how the digital economy influences manufacturing innovation.

1.3. Research Assumptions

1.3.1. The Perspective of Regional Innovation System (RIS)

From the perspective of RIS theory, the digital economy impacts manufacturing innovation performance by reshaping the regional innovation ecosystem. Huang Zelin et al. (2022) found that the digital economy facilitates technological diffusion and knowledge spillover by improving regional digital infrastructure and innovation networks. Yu Feifei et al. (2022) noted that the impact of regional digitalization on corporate innovation exhibits non-linear characteristics, subject to a "Capability-Environment" matching threshold. Xu Hui et al. (2022) observed that the promoting effect of the digital economy on innovation is more pronounced in regions with well-established innovation systems. Furthermore, Zheng Puyang et al. (2022) proposed that differences in resource allocation efficiency across regions affect the realization of the digital economy's innovation effects. Based on this analysis, the following hypothesis is proposed:

H1: The digital economy has a direct promoting effect on manufacturing innovation performance.

1.3.2. The Perspective of Dynamic Capabilities (DC)

From the perspective of DC theory, the digital economy influences innovation performance by stimulating enterprise dynamic capabilities. Li Feng et al. (2023) pointed out that digital infrastructure not only provides technological support but also enhances enterprises' ability to sense market changes through data integration. Pan Peiyao et al. (2023), focusing on the platform economy, found that digital platforms reinforce enterprises' capabilities in resource integration and reconfiguration. Wang Lijing et al. (2021), through a multi-case study, discovered that enterprises need to develop new capability combinations adapted to the digital environment to breach innovation boundaries. Jia Jianfeng et al. (2022) further demonstrated that enterprise dynamic capabilities play a key mediating role between digital transformation and innovation performance. Accordingly, this paper proposes the following hypotheses:

H2: The development of the digital economy promotes manufacturing innovation performance by enhancing resource allocation efficiency.

H3: The digital economy promotes manufacturing innovation performance by reinforcing enterprise dynamic capabilities.

1.4. Summary

Summary Synthesizing the above, RIS theory suggests that systemic differences may exist in the institutional environment, industrial foundation, and digital facilities across different regions; meanwhile, DC theory indicates that enterprises' responsiveness to external digital opportunities also varies depending on regional conditions. Consequently, the impact of the digital economy on manufacturing innovation performance is likely to exhibit regional heterogeneity. This theoretical logic constitutes the foundation for the heterogeneity analysis presented later in this study.

2. Research Design

2.1. Variable Selection and Data Description

2.1.1. Dependent Variable: Manufacturing Innovation Performance

Corporate innovation performance refers to the actual achievements obtained by an enterprise or region during the implementation of technological innovation, including new product development, patent output, and R&D input-output efficiency. Existing literature primarily measures this using metrics such as Tobin's Q (Liu Jianjiang et al., 2024), scales (Ahuja et al., 2001), and the number of inventions (Dai Senzhi et al., 2024). Following relevant studies by Yang Gening et al. (2022) and Feng Shizheng et al. (2023), this paper selects the total number of granted patents in each province as the observational indicator for innovation performance. To ensure data stationarity and reduce heteroscedasticity, the natural logarithm of this value is taken, denoted as *inn*.

2.1.2. Core Independent Variable: Development Level of Digital Economy *dig_{it}*

Drawing on research by Xu Qingyuan (2018) and Luo Ruixue et al. (2024), this paper constructs a comprehensive evaluation system to assess the digital economy development level of provincial regions in China. The system encompasses four dimensions: Digital Infrastructure, Industrial Application, Digital Industrialization, and Digital Financial Inclusion.

The equal-weight method is applied between the primary dimensions. Several secondary indicators are standardized into the [0,1] interval using Min-Max Normalization. Subsequently, the Entropy Weight Method is employed to assign specific weights. Finally, the resulting scores are multiplied by 100 to standardize the comprehensive index into the [0,100] interval, facilitating horizontal comparison and time-series analysis. The specific indicators are detailed in Table 1.

Table 1. Measurement Indicators of Digital Economy Development

Primary Indicators	Secondary Indicators	Unit	Weight
Digital Infrastructure	Mobile phone penetration rate	Sets/100 people	0.0319
	Broadband internet access ports	10,000 units	0.0432
	Computers per 100 people	Sets	0.0432
	Mobile internet access traffic	10,000 GB	0.0875
	Mobile internet users	10,000 households	0.0442
Industrial Digitization	Number of enterprises with e-commerce transactions	Units	0.0424
	Number of websites per 100 enterprises	Units	0.0093
	E-commerce sales volume	100 million CNY	0.0630
	Proportion of enterprises with e-commerce transactions	%	0.0140
	R&D expenditure of industrial enterprises above designated size	10,000 CNY	0.0518
	Number of new product projects in industrial enterprises above designated size	Items	0.0696
Digital Industrialization	Revenue from information technology services	10,000 CNY	0.0428
	Revenue from embedded system software	10,000 CNY	0.0778
	Software business exports	10,000 USD	0.0615
	Software business revenue	10,000 CNY	0.0403
	Number of enterprises in electronic and communication equipment manufacturing	Units	0.0276
Digital Financial Inclusion	Breadth of coverage	/	0.0989
	Depth of usage	/	0.0599
	Level of digitization	/	0.0912

2.1.3. Mediator Variable

Resource Allocation Efficiency Zhang Jun et al. (2004) pointed out that resource allocation efficiency is manifested as the degree of convergence in marginal returns among various production factors, serving as a core indicator for measuring the optimization of resource usage in a region or industry. Currently, mainstream academia predominantly adopts Total Factor Productivity (TFP) as a proxy variable for resource allocation efficiency. Following the methodology of Brandt et al. (2012) and Xu Helian (2020), this paper utilizes the Solow Residual Method to construct the TFP index at the provincial level. In the TFP model, inputs include capital (K_{it}) and labor (L_{it}), while output is represented by regional GDP (Y_{it}). The TFP level changes are identified through the residual component of the log-linear regression. The specific model is as follows:

$$\ln TFP_{it} = \ln Y_{it} - \alpha \ln K_{it} - \beta \ln L_{it}$$

Where Y_{it} represents the output (Regional GDP) of region i in t year. K_{it} denotes capital input (measured by fixed asset investment); L_{it} denotes labor input (year-end number of employed persons); and α, β represent the output elasticities of capital and labor, respectively.

2.1.4. Data Description

To ensure data accessibility and consistency, this paper selects 11 provincial administrative units in China's Yangtze River Economic Belt from 2015 to 2023 to analyze the impact of the digital economy on manufacturing innovation performance.

Dependent Variable Data: Sourced from the Annual Statistical Report of the National Intellectual Property Administration, cross-validated with the China Regional Science and Technology Statistical Yearbook and provincial statistical communiqués. Independent Variable Data: Sourced from the National Bureau of Statistics, Peking University Digital Finance Research Center, CNKI, and Mark Data Network. Mediator Variable Data: Regional GDP (current prices), Total Fixed Asset Investment, and Year-end Employed Persons are sourced from the China Statistical Yearbook, China Labour Statistical Yearbook, and China Statistical Yearbook on Fixed Asset Investment, respectively. Missing data for certain years were supplemented using Linear Interpolation.

3. Empirical Analysis

This study systematically investigates the impact of the digital economy on manufacturing innovation performance using the Structural Equation Model (SEM) and examines the mediating role of resource allocation efficiency within the empirical path. To ensure the reliability of the conclusions, we successively conducted baseline regression, mediation effect tests, model fit assessment, and robustness tests via grouping. The descriptive statistics of the variables are presented in Table 2.

Table 2. Descriptive Statistics of Variables

Variable	N	Mean	Std	Min	Max
inn_{it} (Innovation)	99	11.252	0.955	9.252	13.371
dig_{it} (Dig. Economy)	99	29.000	16.790	6.700	83.900
re_{it} (Resource Eff.)	99	0.005	0.448	-0.733	0.925

3.1. Structural Equation Model (SEM) Analysis

3.1.1. Baseline Regression and Mediation Analysis

First, this paper employs SEM to analyze the path relationships among the digital economy, resource allocation efficiency, and manufacturing innovation performance. The results are shown in Table 3.

Table 3. Path Coefficient Estimation Results of SEM

Path Relationship	Coefficient	Robust Std. Err.	z-value	P> z
Digital Economy $\Rightarrow$ Resource Allocation Eff.	1.015***	0.283	3.59	0.000
Resource Allocation Eff. $\Rightarrow$ Innovation Perf.	0.500***	0.066	7.58	0.000
Digital Economy $\Rightarrow$ Innovation Perf.	0.820***	0.062	13.27	0.000

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

Table 3 reveals the path coefficient estimation results. The findings indicate that the digital economy drives the improvement of manufacturing innovation performance through two paths: direct empowerment and indirect optimization.

In terms of the direct effect, the digital economy exhibits a strong direct promoting effect on manufacturing innovation performance ($\beta = 0.820$, $p < 0.01$). This suggests that digital technology, as a General Purpose Technology (GPT), inherently functions as a powerful driver of innovation empowerment, profoundly reshaping the manufacturing innovation paradigm. Specifically, the deep integration of the industrial internet, AI, and big data allows enterprises to iterate product designs based on real-time data feedback, optimize production processes through simulation, and achieve open innovation with user participation via platform ecosystems. Consequently, this significantly compresses R&D cycles, reduces trial-and-error costs, and directly spawns technological innovation and product upgrades.

Regarding the mediation path, first, the digital economy significantly optimizes resource allocation efficiency ($\beta = 1.015$, $p < 0.01$). This underscores that the profound economic value of the digital economy lies in its fundamental transformation of traditional factor allocation. Digital platforms break information barriers, facilitating the efficient market-oriented matching of innovation factors-such as capital, talent, and technology-across regional and even national scales. Simultaneously, as a new key factor of production, the flow and sharing of data further enhance Total Factor Productivity (TFP), accelerating the transfer of scarce resources from low-efficiency sectors to high-efficiency ones. Subsequently, resource allocation efficiency demonstrates a significant positive impact on manufacturing innovation performance ($\beta = 0.500$, $p < 0.01$), indicating that precise allocation of resources to the most innovative fields and enterprises is key to enhancing overall regional innovation output.

To further quantify the relative importance of these two paths, we conducted a mediation effect test. The results from both the Bootstrap method and the Delta method are highly consistent, confirming the statistical significance of the mediation effect (Effect Size = 0.507, $p < 0.01$). Decomposing the total effect (1.327) reveals that the direct effect accounts for 61.8%, highlighting the dominant role of the digital economy itself as an innovation engine; the indirect effect accounts for 38.2%, revealing that the optimization of resource allocation efficiency is an indispensable intrinsic mechanism. The results suggest that these two paths complement each other, constituting a "Dual-Drive" model for high-quality manufacturing development.

3.1.2. Model Fit Assessment

To determine the match between the theoretical model and the data, key fit indices were obtained. Although some overall fit indices are limited due to the use of clustered robust standard errors, the residual-based fit indicators perform well. The Standardized Root Mean

Square Residual (SRMR) is 0.000, and the Coefficient of Determination (R^2) is 0.765, indicating that the model explains 76.5% of the variation in the dependent variable, demonstrating strong explanatory power. Thus, the model specification is acceptable.

3.2. Spatial Durbin Model

3.2.1. Spatial Correlation Test

Based on panel data from 11 provinces in the Yangtze River Economic Belt (2015–2023), this study finds significant regional heterogeneity in both digital economy development and innovation performance, characterized by the downstream region leading while the upstream and midstream regions are in a catch-up phase. Preliminary analysis of spatial evolution suggests spatial correlation in both variables.

3.2.2. Global Spatial Autocorrelation Test

The Global Moran's I indices for manufacturing innovation performance (2015–2023) are all positive and increasing annually (see Table 4), passing significance tests. This indicates significant spatial agglomeration and dependence. Local Moran scatter plots suggest a "High-High" and "Low-Low" clustering pattern, reflecting a "Strong East, Weak West" configuration.

Table 4. Global Moran's I Index of Manufacturing Innovation Performance (2015-2023)

Year	2015	2016	2017	2018	2019
Moran's I	-0.003*	0.014**	0.029**	0.023**	0.033**
Year	2020	2021	2022	2023	/
Moran's I	0.027**	0.023**	0.046**	0.069***	/

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

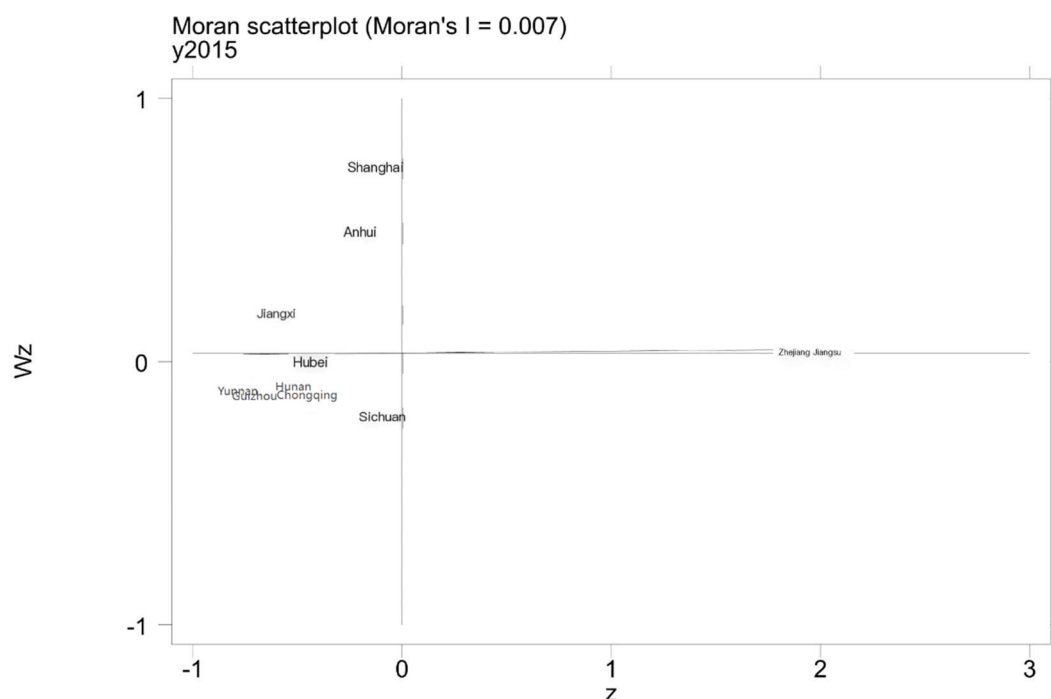


Figure 1. Partial Molain scatterplot of 2015

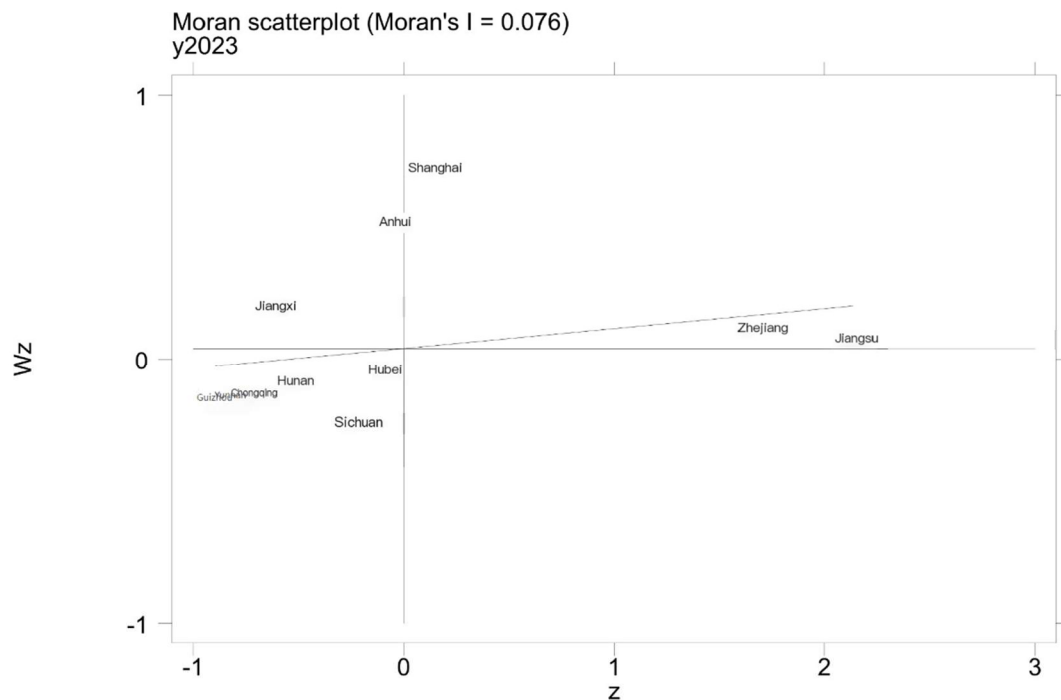


Figure 2. Partial Molain scatterplot of 2023

3.2.3. Selection and Inspection of Spatial Econometric Models

Following Luc Anselin's methodology, model selection proceeds from OLS to LM tests (Lagrange Multiplier). As shown in Table 5, LM statistics are significant at the 1% level, confirming the existence of spatial error and spatial lag effects. The Hausman test supports the Fixed Effects model. Furthermore, Wald and LR tests (see Table 6) reject the null hypothesis that the SDM degrades into SAR or SEM. Therefore, the Spatial Durbin Model (SDM) with two-way fixed effects is selected.

Table 5. Spatial Econometric Regression Results

Variable	Regression coefficient	P-value
dig	0.0488***	0.000
R^2	0.7361	
Test method	statistic	P-value
LM test no spatial error	25.257***	0.000
Robust LM test no spatial error	39.639***	0.000
LM test no spatial lag	0.438	0.508
Robust LM test no spatial lag	14.811***	0.000

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

Table 6. Results of Hausman Test, Wald Test, LR Test

Test method	Statistic	P-value
LR Lag	4.72**	0.0298
LR Err	5.03**	0.0249
Wald Lag	8.28***	0.004
Wald Err	14.57***	0.000
Hausman	24.01***	0.000

3.2.4. Estimation Results and Analysis of SDM

According to the results in Table 7, the spatial autocorrelation coefficient (ρ) is 1.391 and significant at the 1% level, indicating significant spatial spillover effects of innovation performance.

The estimated coefficient of the core independent variable, Digital Economy (dig), is -0.006 (significant at 10%), suggesting an inhibitory effect. To accurately quantify this, we used the Partial Differentiation Method to decompose the effects into Direct, Indirect, and Total effects.

The decomposition results show that the Direct Effect of the digital economy is inhibitory (-0.010), while the Indirect Effect (0.019) and Total Effect (0.009) are promoting. The negative direct effect combined with a positive indirect effect implies a "Siphon Effect" due to factor competition among neighboring regions, yet the overall spillover benefits of the digital network ultimately drive regional development.

Table 7. Spatial Econometric Regression Results

Variable	SDM Coefficient	Direct Effect	Indirect Effect	Total Effect
dig	-0.006*	-0.010**	0.019***	0.009*
	(-1.87)	(-2.28)	(-2.66)	(-1.93)
ρ	1.391***			
	(-4.16)			
R^2	0.012	0.012	0.012	0.012
Fixed Effects	Individual & Time	Individual&Time	Individual&Time	Individual&Time
N	99	99	99	99

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

3.3. Heterogeneity Analysis

To explore the transmission mechanism across different development stages, the sample was divided into "High Digital Economy" ($\ln x > 3.253$) and "Low Digital Economy" ($\ln x \leq 3.253$) groups based on the median. This division aims to capture the stage transition from infrastructure construction to deep application.

Table 8. Heterogeneity Analysis Results

Sample Group	Mediation Effect	Std. Err.	z-value	P> z	95% Conf. Interval
High Digital Group	1.036***	0.215	4.82	0.000	[0.615, 1.458]
Low Digital Group	0.283*	0.162	1.75	0.080	[-0.034, 0.600]

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

The results in Table 8 reveal significant heterogeneity, confirming a non-linear threshold effect. In the High Digital Group, the mediation effect is robust (1.036, $p < 0.01$). This indicates that once the digital economy surpasses a critical threshold (index value approx. 25.87), the transmission path of optimizing resource allocation becomes highly effective. Digital technology transforms from a mere tool into a systemic infrastructure, reshaping factor flow networks.

Conversely, in the Low Digital Group, the mediation effect drops to 0.283 with weak significance. This suggests that in the early stages, the empowering role of the digital economy is limited to localized efficiency improvements, failing to activate the systemic resource reconfiguration needed for regional innovation. This finding validates the "Quantity leads to Quality" logic in digital transformation.

4. Conclusion and Policy Implications

4.1. Conclusion

Based on panel data from 11 provinces in the Yangtze River Economic Belt (2015–2023), this study comprehensively employs the Spatial Durbin Model (SDM), Structural Equation Modeling (SEM), and Grouping Regression to systematically investigate the impact mechanisms, spatial effects, and boundary conditions of the digital economy on manufacturing innovation performance. The main conclusions are as follows:

First, the digital economy not only directly empowers manufacturing innovation but also generates a significant mediating effect by enhancing regional resource allocation efficiency. SEM results indicate that the direct effect of the digital economy on manufacturing innovation performance is 0.820, while the indirect effect transmitted through resource allocation efficiency is 0.507, yielding a total effect of 1.327. This suggests that within the Yangtze River Economic Belt, the digital economy has become a crucial engine driving manufacturing innovation. Its role is manifested not merely through the direct pull of technological penetration and process reengineering but, more importantly, through the systemic optimization of the allocation efficiency of factors such as capital, talent, and data.

Second, the impact of the digital economy on manufacturing innovation performance exhibits significant spatial spillover and regional competition characteristics. SDM estimates show that the direct effect of the digital economy manifests as a slight inhibitory action locally, whereas its spatial lag coefficient is significantly positive, indicating strong positive spatial spillovers. This finding reflects that, against the backdrop of unbalanced regional development, the development of the digital economy may initially induce a cross-regional absorption of innovation factors, forming a "Siphon Effect." Consequently, this manifests locally as a short-term crowding out of innovation resources.

Third, the transmission mechanism by which the digital economy influences innovation performance via resource allocation efficiency possesses distinct non-linear threshold characteristics. Grouping regression results demonstrate that the mediating path becomes fully significant and robust only after the digital economy development level surpasses a specific threshold. In regions above this threshold, the intensity of the mediation effect reaches 1.036; conversely, in regions below the threshold, the effect drops to 0.283 with substantially weakened statistical significance. This reveals that the empowerment of innovation performance by the digital economy is not linearly universal; the realization of its resource allocation optimization function is contingent upon the maturity of digital infrastructure, the data factor market, and the technological application ecosystem.

4.2. Policy Implications

Based on the above conclusions, to promote the deep integration of the digital economy and manufacturing and to foster coordinated regional innovation development, this paper proposes the following policy recommendations:

First, implement a differentiated and tiered digital economy development strategy. Policymakers should recognize the disparities in regional digital foundations and avoid a "one-size-fits-all" approach. For regions with high levels of digital economy: The focus should be on deepening the construction of the data factor market and promoting the fusion of industrial internet platforms with regional innovation networks, thereby further smoothing the transmission mechanism of "Digital Technology - Factor Allocation - Industrial Innovation." For regions with lower development levels: The priority is to solidify digital infrastructure and reduce the costs of digital transformation for enterprises. Through pilot demonstrations and the establishment of public service platforms, these regions should be assisted in surpassing the threshold of digital empowerment.

Second, establishing a cross-regional innovation collaboration and benefit-balancing mechanism. To mitigate the potential competition for innovation factors caused by the digital economy development (i.e., the Siphon Effect), efforts should be made to build a regional collaborative governance system characterized by "clear responsibilities and shared benefits." Actionable Measures: Establish a Digital Technology Innovation Alliance for the Yangtze River Economic Belt and set up cross-provincial digital cooperation demonstration zones. These initiatives will facilitate the orderly flow and efficient allocation of innovation factors-such as knowledge, technology, and data-effectively transforming spatial spillover effects into a combined force for regional collaborative innovation.

Third, strengthen policy evaluation and guidance centred on resource allocation efficiency. When assessing the effectiveness of digital economy development, beyond focusing on infrastructure investment and industrial scale, a monitoring system centered on Resource Allocation Efficiency (e.g., Total Factor Productivity, convergence of marginal factor output) should be established. Policy tools should focus more on eliminating institutional barriers to factor mobility, activating the potential of data elements, and guiding financial capital and R&D resources to aggregate towards advanced manufacturing sectors, thereby tangibly enhancing the systemic efficacy of the digital economy in serving real economy innovation.

Forth, promote the formation of a tripartite support system comprising digital infrastructure, platform ecosystems and enterprise capabilities. The government should coordinate the layout of new infrastructure such as 5G and computing power networks, while encouraging platform-based enterprises to open up their technological capabilities and data resources. Simultaneously, through tax incentives and innovation vouchers, manufacturing enterprises-especially SMEs-should be incentivized to enhance their dynamic capabilities in data governance, process reengineering, and cross-boundary integration. This will foster a virtuous cycle where infrastructure supports platforms, platforms empower enterprises, and enterprises feed back into the ecosystem.

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