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Empowering Manufacturing Industry Chain Resilience Through Digital-Intelligence Integration: A Resource Orchestration and Dynamic Capabilities Perspective

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Abstract: In the context of escalating global supply chain disruptions, geopolitical fragmentation, and rapid technological change, enhancing the resilience of the manufacturing industry chain has become a critical strategic priority for major industrial economies. This study investigates the theoretical mechanisms and empirical impacts of Digital-Intelligence Integration (DI)—the deep, synergistic fusion of digital infrastructures and intelligent technologies—on manufacturing industry chain resilience. We establish an analytical framework drawing upon Dynamic Capabilities Theory and Resource Orchestration Theory to explain how DI builds systemic adaptive capacity. Using a balanced panel dataset of 31 Chinese provinces over the period 2011–2024, we construct comprehensive evaluation indices for DI and manufacturing resilience using the Quadratic Entropy Method, which incorporates time-dimension information entropy to ensure dynamic consistency. Utilizing a two-way fixed-effects panel model, our baseline regressions reveal that DI significantly promotes manufacturing industry chain resilience. This positive relationship remains robust across multiple verification tests, including the exclusion of the COVID-19 pandemic year, the exclusion of direct-controlled municipalities, one-period lagged independent variables, and alternative measurements of resilience. To address endogeneity, we employ two-stage least squares (2SLS) estimation using legacy post office density in 1984 and capital-to-coast geographic distance as external instruments. Sub-dimensional analyses show that the driving power of the industry chain receives the largest enhancement from DI, followed by stabilizing power and recovery power, as confirmed by Seemingly Unrelated Regression (SUR) Wald tests. Mechanism analysis indicates that DI fosters resilience through three main channels: stimulating breakthrough innovation, optimizing the business environment, and promoting industrial agglomeration. Geographic and development heterogeneity tests show that the resilience-enhancing effect of DI is most pronounced in the Central region, in high-DI adoption areas, and in regions with high levels of industrial agglomeration. These findings provide empirical support and policy implications for utilizing digital-intelligence technologies to secure supply chain stability and promote high-quality industrial development.

Keywords: digital-intelligence integration, manufacturing industry chain resilience, resource orchestration, dynamic capabilities, regional heterogeneity

1. Introduction

The contemporary global economy is experiencing a period of intense structural adjustment, restructuring, and high volatility. Manufacturing systems worldwide are facing complex challenges arising from geopolitical conflicts, trade protectionism, supply chain decoupling pressures, and public health crises. These disruptions have

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exposed structural vulnerabilities in traditional manufacturing networks, resulting in supply shortages, logistical bottlenecks, and production stoppages. Concurrently, a new round of technological revolution and industrial transformation is advancing rapidly. The convergence of digital infrastructure and intelligent technologies—referred to as Digital-Intelligence Integration (DI)—is reshaping the organizational boundaries, production logics, and competitive landscapes of global manufacturing (Aslam et al., 2025; Chen et al., 2025; Guo et al., 2025; Ivanov, 2023).

In this environment, ensuring industry chain resilience has emerged as a core policy objective for industrial economies. We define industry chain resilience as the capacity of an industrial system to withstand external shocks, maintain structural integrity, recover operations swiftly, and transition toward higher-value states (Boschma, 2015; Martin, 2012). Traditional risk management strategies, such as maintaining high inventory levels, dual sourcing, or localized redundancy, impose substantial carrying costs and are insufficient to counter systemic disruptions. DI offers a dynamic, information-driven alternative. By embedding industrial IoT, big data analytics, cloud computing, and intelligent decision-making systems across the value chain, DI enables real-time sensing, collaborative coordination, and adaptive response capabilities.

Despite the growing consensus on the value of digital transformation, empirical research systematically analyzing the combined effect of digitalization and intelligentization on macro-level manufacturing industry chain resilience remains limited. Existing literature has explored the role of digitalization or artificial intelligence individually on firm performance or supply chain agility. However, these studies often treat digitalization and AI as separate technical elements rather than a synergistic, co-evolving socio-technical system. Furthermore, the underlying management mechanisms through which these technologies translate into systemic macro-level resilience remain a "black box" in the literature.

To address these gaps, this study integrates Dynamic Capabilities Theory (DCT) and Resource Orchestration Theory (ROT) to examine how DI enhances manufacturing industry chain resilience. Using the Quadratic Entropy Method on panel data from 31 Chinese provinces from 2011 to 2024, we measure provincial DI levels and manufacturing resilience—decomposed into stabilizing power, recovery power, and driving power. Using a two-way fixed-effects model, we establish the direct impact of DI on resilience, investigate three transmission channels (breakthrough innovation, business environment, and industrial agglomeration), and analyze regional and development heterogeneities.

Our study makes several contributions to the literature. First, we construct a comprehensive evaluation framework that captures the synergistic interaction between digitalization and intelligentization, providing a more integrated measure of technology adoption. Second, we decompose manufacturing industry chain resilience into stabilizing power, recovery power, and driving power, and empirically verify that DI has a differentiated impact across these dimensions. Third, we systematically test three transmission channels (technological, institutional, and spatial), unpacking the "black box" of how technology adoption translates into systemic resilience.

The remainder of this study is organized as follows. Section 2 discusses the theoretical background and develops research hypotheses. Section 3 describes the variables, data sources, and econometric methodology. Section 4 presents the baseline regression results, robustness checks, and endogeneity corrections. Section 5 evaluates the transmission mechanisms. Section 6 conducts heterogeneity analyses, and Section 7 concludes with policy recommendations.

2. Literature Review and Research Hypotheses

2.1 Digital-Intelligence integration and industry chain resilience: a resource orchestration and dynamic capabilities perspective

To understand how Digital-Intelligence Integration (DI) enhances industrial resilience, we draw upon two foundational frameworks in general management theory: Dynamic Capabilities Theory (DCT) (Teece et al., 1997; Eisenhardt and Martin, 2000) and Resource Orchestration Theory (ROT) (Sirmon et al., 2007, 2011), both rooted in the Resource-Based View (Barney, 1991, 2001; Wernerfelt, 1984). In general management, dynamic capabilities represent an organization's (or an industrial network's) ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments. In this study, we argue that manufacturing industry chain resilience—decomposed into stabilizing power, recovery power, and driving power—is the macro-level manifestation of dynamic capabilities aggregated across the industrial ecosystem.

Resource Orchestration Theory further clarifies how these capabilities are constructed. ROT posits that simply possessing resources does not guarantee competitive advantage or resilience; rather, managers must actively structure the resource portfolio, bundle resources to build capabilities, and leverage these capabilities to execute strategies. Within this framework, DI represents a systematic process of resource orchestration:

First, the structuring phase involves selecting and acquiring digital assets. Digitalization represents this structuring phase, where firms and regional networks invest in digital infrastructures (e.g., 5G base stations, fiber optic networks, cloud computing databases, IoT sensors) to assemble a robust data resource portfolio. This phase establishes the baseline connectivity and visibility of the manufacturing network.

Second, the bundling phase involves integrating assets to form capabilities. Intelligentization represents this bundling phase, where advanced algorithmic tools, machine learning models, cloud services, and ERP systems are integrated with the physical database. This turns raw data into actionable decision-making assets, allowing firms to identify anomalies, predict shortages, and optimize production schedules.

Third, the leveraging phase involves deploying these capabilities to execute strategies. The integrated DI system is leveraged to optimize resource allocation, coordinate workflows, and make predictive decisions. Under volatile market demands or geopolitical supply disruptions, this orchestration enables the system to re-route logistics, coordinate alternative suppliers, and dynamically configure production processes.

Through this resource orchestration process, the manufacturing industry chain builds the dynamic capabilities necessary to enhance resilience across three dimensions:

Stabilizing Power: By structuring and bundling information resources, DI minimizes information latency and demand distortion (the bullwhip effect). This enables the manufacturing network to maintain output stability, balance inventories, and protect capital structures under external demand and supply shocks.

Recovery Power: When disruptions occur, DI leverages alternative supplier matching and flexible production reallocation. This allows the system to rapidly reconfigure its operations, coordinate emergency logistics, and ease short-term financing constraints, minimizing recovery times.

Driving Power: DI integrates external knowledge pools and advanced technology inputs. This enables the industry chain to actively upgrade its structure, transition toward high-tech activities, improve green efficiency, and achieve green total factor productivity growth.

According to DCT, dynamic capabilities are most critical for long-term strategic transformation and path breakthrough rather than routine operations. Therefore, the orchestration of DI resources should yield the greatest marginal benefits for the driving power dimension, which represents active adaptation and upgrading.

Hypothesis H1: Digital-Intelligence Integration (DI) significantly enhances manufacturing industry chain resilience, with the largest marginal effect observed on the driving power dimension.

2.2 Transmission mechanisms of DI

DI does not influence manufacturing resilience in isolation; it restructures the micro-technological, macro-institutional, and meso-spatial environments of the manufacturing ecosystem. We identify three distinct transmission channels:

2.2.1 Breakthrough innovation channel (Micro-level)

Technological innovation is the primary driver of industrial upgrading and resilience. In evolutionary geography, breakthrough innovation—as opposed to incremental improvements—allows industry chains to bypass path dependency, escape technological lock-in, and overcome external bottlenecks. DI facilitates breakthrough innovation by:

Reducing knowledge search costs through digital repositories and high-speed collaboration networks (Grant, 1996).

Lowering R&D failure risks through digital twins and AI-driven simulation platforms.

Supporting cross-regional, multi-organizational joint research projects.

Fostering breakthrough innovations helps regions secure proprietary core technologies, protecting the industry chain from external trade blockades.

Hypothesis H2a: DI enhances manufacturing industry chain resilience by stimulating breakthrough innovation.

2.2.2 Business environment channel (Macro-level)

The quality of the business environment determines transaction costs and resource allocation efficiency. DI optimizes this institutional foundation in two ways:

Administrative efficiency: Digital government platforms simplify administrative approvals, reducing institutional transaction costs.

Financial accessibility: Big data and algorithmic credit evaluations alleviate credit constraints for small- and medium-sized manufacturing firms, providing financial buffers that support post-shock recovery (Wang and Duan, 2025).

A highly efficient business environment attracts high-quality foreign direct investment, fosters market trust, and provides institutional buffers that enhance industry chain stabilization and recovery.

Hypothesis H2b: DI enhances manufacturing industry chain resilience by optimizing the business environment.

2.2.3 Industrial agglomeration channel (Meso-level)

Spatial concentration of firms generates localized knowledge spillovers, labor pooling, and shared input access. DI promotes industrial agglomeration by lowering geographical transaction costs through digital marketplaces and platforms. Within digitally integrated clusters, manufacturing firms benefit from collaborative capacity sharing ("shared slack"), rapid supplier substitution, and the localized diffusion of crisis-management knowledge, all of which mitigate supply chain vulnerability (He et al., 2024).

Hypothesis H2c: DI enhances manufacturing industry chain resilience by fostering industrial agglomeration.

3. Variable Measurement, Data, and Methodology

3.1 Indicator construction and evaluation method

To capture the dynamic features of DI and resilience across time and regions, we utilize the Quadratic Entropy Method. Unlike the static entropy method, the Quadratic Entropy Method incorporates time-dimension information entropy to ensure dynamically consistent weights for panel data comparisons. The normalized indicators are weighted based on their dynamic information utility.

3.1.1 Digital-Intelligence integration (DI)

The DI index is constructed from 12 indicators across two sub-dimensions: Digitalization (representing digital infrastructure and basic applications) and Intelligentization (representing AI, advanced algorithms, and smart applications). The index system is detailed in Table 1.

Table 1: Digital-Intelligence Integration (DI) Index System

Dimension	Sub-Dimension	Indicator	Direction
DI Index	Digitalization	Mobile phone penetration rate (phones per 100 people)	+
DI Index	Digitalization	Optical fiber cable length (km per capita)	+
DI Index	Digitalization	Internet domains per 10,000 people	+
DI Index	Digitalization	E-commerce transaction volume (normalized)	+
DI Index	Digitalization	Enterprise ERP adoption rate (%)	+
DI Index	Digitalization	ICT equipment investment (million RMB)	+
DI Index	Digitalization	Digital economy patent applications (count)	+
DI Index	Intelligentization	Industrial robot installations (units per 10,000 workers)	+
DI Index	Intelligentization	Smart manufacturing pilot projects (count)	+
DI Index	Intelligentization	AI patent applications (count)	+
DI Index	Intelligentization	Cloud computing service market size (billion RMB)	+
DI Index	Intelligentization	Big data enterprise count (count)	+

3.1.2 Manufacturing industry chain resilience (RES)

Resilience is measured across 12 indicators representing Stabilizing Power (SP), Recovery Power (RP), and Driving Power (DP), as detailed in Table 2.

Table 2: Manufacturing Industry Chain Resilience (RES) Index System

Dimension	Sub-Dimension	Indicator	Direction
Resilience (RES)	Stabilizing Power (SP)	Manufacturing output volatility	-
Resilience (RES)	Stabilizing Power (SP)	Asset-liability ratio (%)	-
Resilience (RES)	Stabilizing Power (SP)	Intermediate goods localization rate (%)	+
Resilience (RES)	Stabilizing Power (SP)	Delivery reliability index	+
Resilience (RES)	Recovery Power (RP)	Emergency production conversion capacity	+
Resilience (RES)	Recovery Power (RP)	Average recovery speed (days)	-
Resilience (RES)	Recovery Power (RP)	Short-term financing liquidity	+

Table 2: Manufacturing Industry Chain Resilience (RES) Index System(Table continuation)

Dimension	Sub-Dimension	Indicator	Direction
Resilience (RES)	Recovery Power (RP)	Alternative supplier matching rate (%)	+
Resilience (RES)	Driving Power (DP)	Manufacturing R&D intensity (%)	+
Resilience (RES)	Driving Power (DP)	High-tech manufacturing share of GDP (%)	+
Resilience (RES)	Driving Power (DP)	Green total factor productivity (GTFP)	+
Resilience (RES)	Driving Power (DP)	Human capital density (years of education)	+

3.2 Econometric model specification

To test the direct impact of DI on manufacturing resilience, we specify the following two-way fixed-effects panel model:

$$RES_{it} = \alpha + \beta\, DI_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where i and t denote province and year, respectively; RES_{it} represents the composite manufacturing industry chain resilience index; DI_{it} denotes the digital-intelligence integration index; X_{it} is a vector of control variables; α is the constant intercept; β represents the core regression coefficient of interest; γ is the vector of coefficients for control variables; μ_i represents province fixed effects; λ_t represents year fixed effects; and ε_{it} is the idiosyncratic random error term. To account for potential serial correlation and heteroscedasticity, standard errors are clustered at the provincial level.

3.3 Data sources and control variables

We use panel data from 31 provinces in mainland China (excluding Hong Kong, Macau, and Taiwan) spanning 2011 to 2024, yielding a balanced panel of 434 observations. Data are sourced from the *China Statistical Yearbook*, the *China Industrial Statistical Yearbook*, patent databases, and provincial statistical bureaus. Missing values are filled using linear interpolation.

To isolate the impact of DI, we control for several regional characteristics:

1. Economic Development (LGDP): Log of per capita real GDP (constant 2011 prices). Higher economic development indicates a larger market capacity and greater financial resources to support industrial upgrades.
2. Environmental Regulation (ER): Log of industrial pollution control investment. Environmental regulation may force firms to upgrade technology (Porter hypothesis) or impose compliance costs.
3. Industrial Structure (IS): The ratio of tertiary industry value added to secondary industry value added. This controls for structural shifts in the economy.
4. Transportation Infrastructure (TI): Per capita road surface area. Physical connectivity is essential for logistical resilience and raw material transportation.
5. Human Capital (HC): Standardized number of university students per 100,000 people. Human capital determines the capacity to absorb new technologies.
6. Opening-up Degree (OD): Foreign direct investment (FDI) share of regional GDP. This captures integration into global markets.

Table 3: Descriptive Statistics

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
RES	Industry Chain Resilience	434	0.104	0.098	0.019	0.677
DI	Digital-Intelligence Level	434	0.169	0.143	0.009	0.903
LGDP	Economic Development	434	0.078	0.041	-0.039	0.285
ER	Environmental Regulation	434	9.733	0.942	7.049	12.143
IS	Industrial Structure	434	1.399	0.768	0.527	5.891
TI	Transportation Infra.	434	6.158	2.440	1.100	14.526
HC	Human Capital	434	0.000	1.000	-1.879	4.079
OD	Opening-up Degree	434	0.413	0.476	0.055	3.556

4. Empirical Results and Robustness Analysis

4.1 Baseline regression results

Table 4 reports the baseline regression results, using a stepwise approach to introduce control variables. Across all specifications, the coefficient on DI is positive and statistically significant at the 1% level. In the full model (Column 7), the coefficient of 0.637 indicates that a one-unit increase in the DI index leads to a 0.637-unit increase in the manufacturing industry chain resilience index ($p < 0.01$).

Looking at the control variables in Column 7:

Economic Development (LGDP): Shows a positive and significant relationship with resilience (coef = 0.548, $p < 0.05$), validating that economic growth provides a solid resource base.

Environmental Regulation (ER): Has a positive coefficient (coef = 0.011), suggesting that regulatory pressure motivates green technological updates, supporting the Porter hypothesis.

Transportation Infrastructure (TI): Has a positive and significant effect (coef = 0.007, $p < 0.05$), confirming that logistics networks are crucial for supply chain continuity.

Human Capital (HC): Exhibits a positive coefficient (coef = 0.021), showing that regions with richer talent pools have stronger adaptive capacities.

Industrial Structure (IS): Has a negative coefficient (coef = -0.015), indicating that an excessive shift away from the secondary sector (deindustrialization) might undermine manufacturing resilience.

Opening-up Degree (OD): Shows a positive relationship (coef = 0.034), confirming that international integration facilitates technical spillovers.

Table 4: Baseline Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DI	0.645*	0.644*	0.644*	0.642*	0.646*	0.643*	0.637*
	(0.099)	(0.098)	(0.098)	(0.099)	(0.099)	(0.100)	(0.103)
LGDP		0.521	0.518	0.519	0.524	0.531	0.548
		(0.245)	(0.246)	(0.246)	(0.247)	(0.248)	(0.251)
ER			0.008	0.007	0.008	0.009	0.011
			(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
IS				-0.012	-0.011	-0.013	-0.015
				(0.015)	(0.015)	(0.015)	(0.016)
TI					0.005	0.006	0.007
					(0.002)	(0.003)	(0.003)
HC						0.018	0.021
						(0.014)	(0.015)
OD							0.034
							(0.028)
Province FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
R^2	0.838	0.839	0.839	0.839	0.839	0.841	0.847
Obs	434	434	434	434	434	434	434

Note: *, , and * denote statistical significance at the 10%, 5%, and 1% levels, respectively. Clustered robust standard errors are in parentheses.

4.2 Sub-Dimensional decomposition analysis

To evaluate how DI influences different facets of resilience, we run regressions using the sub-dimensional indices—Stabilizing Power (SP), Recovery Power (RP), and Driving Power (DP)—as dependent variables. The results are reported in Table 5. The estimated coefficients show that DI has a positive and significant effect on all three dimensions.

Notably, the coefficient for Driving Power (coef = 0.294) is larger than those for Stabilizing Power (coef = 0.176) and Recovery Power (coef = 0.168). Seemingly Unrelated Regression (SUR) Wald tests confirm that the impact on Driving Power is statistically larger than the other two ($p < 0.01$). This confirms that DI primarily drives resilience by promoting long-term structural upgrading, innovation capability, and green productivity (driving power) rather than simple passive stabilization, validating Hypothesis H1.

Table 5: Sub-Dimensional Decomposition Results

	(1) Stabilizing Power (SP)	(2) Recovery Power (RP)	(3) Driving Power (DP)
DI	0.176*	0.168*	0.294*
	(0.038)	(0.043)	(0.053)
Controls	YES	YES	YES
Province/Year FE	YES	YES	YES
Obs	434	434	434
SUR Wald Test	SP = RP: $p > 0.10$	DP > SP: $p < 0.01$	DP > RP: $p < 0.01$

4.3 Robustness checks

To verify the stability of our baseline estimates, we conduct several robustness tests:

1. Excluding the Pandemic Year (2020): To address potential anomalies caused by COVID-19, we run the regression excluding 2020 data.
2. Excluding Municipalities: We exclude the four direct-controlled municipalities (Beijing, Tianjin, Shanghai, Chongqing) to minimize administrative bias.
3. Lagged DI: We use the one-period lagged DI (DIi,t-1) to mitigate reverse causality.
4. Alternative Resilience Measure: We reconstruct the resilience index by excluding scale-dependent indicators to control for scale bias.

As shown in Table 6, across all tests, the DI coefficient remains positive and statistically significant at the 1% level, confirming the robustness of the baseline findings.

Table 6: Robustness Tests

	(1) Excl. 2020	(2) Excl. Municipalities	(3) Lagged DI	(4) Alt. Resilience
DI / Lagged DI	0.694*	0.717*	0.643*	0.736*
	(0.089)	(0.059)	(0.113)	(0.141)
Controls	YES	YES	YES	YES
Province & Year FE	YES	YES	YES	YES
Obs	403	378	403	434
R^2	0.844	0.861	0.846	0.812

4.4 Endogeneity corrections

To address potential endogeneity issues arising from omitted variables and measurement errors, we employ two-stage least squares (2SLS) estimation. Following existing literature, we use two instrumental variables (IVs):

IV1: The interaction between the geographic distance from a province's capital to the nearest major seaport and the lagged national DI level.

IV2: The interaction between the historical post office density in 1984 (representing legacy communication infrastructure) and the lagged national DI level.

Table 7 reports the 2SLS results. The first-stage Kleibergen-Paap LM and Cragg-Donald Wald F statistics reject the underidentification and weak instrument hypotheses. In the second stage, the coefficients on the instrumented DI variable remain positive and statistically significant at the 1% level, demonstrating that our baseline findings are robust to endogeneity concerns.

Table 7: Two-Stage Least Squares (2SLS) Estimation Results

	(1) IV1: Coastal Distance × Lagged National DI	(2) IV2: 1984 Post Density × Lagged National DI
	Second Stage (RES)	Second Stage (RES)
DI (Instrumented)	0.687*	0.776*
	(0.070)	(0.124)
Controls	YES	YES
Province & Year FE	YES	YES
Kleibergen-Paap LM	44.454*	26.704*
Cragg-Donald F	50.934	147.948
Obs	403	403

5. Transmission mechanism analysis

To test Hypothesis H2, we analyze the mediating pathways through which DI influences resilience using a mediation model:

$$Mit = \alpha 0 + \delta\ DIit + \gamma'\ Xit + \mu i + \lambda t + \varepsilon it \quad (2)$$

where Mit represents the mediator variables: breakthrough innovation (measured by the number of green and high-tech invention patents), business environment (measured by the Wang and Fan index), and industrial agglomeration (measured by the location quotient of manufacturing).

The results are reported in Table 8.

Column 1 shows that DI has a positive and significant effect on breakthrough innovation (coef = 3.647, $p < 0.01$). This validates H2a, confirming that DI provides the digital tools, simulators, and data platforms necessary to support high-tech knowledge generation.

Column 2 confirms that DI significantly improves the business environment index (coef = 1.952, $p < 0.01$). This validates H2b, indicating that DI simplifies administrative workflows and improves credit information sharing.

Column 3 demonstrates that DI promotes industrial agglomeration (coef = 0.575, $p < 0.01$). This validates H2c, confirming that digital coordination platforms lower spatial transaction costs, reinforcing spatial clustering.

Table 8: Transmission Mechanism Regressions

	(1) Breakthrough Innovation	(2) Business Environment	(3) Industrial Agglomeration
DI	3.647*	1.952*	0.575*
	(0.890)	(0.580)	(0.206)
Controls	YES	YES	YES
Province & Year FE	YES	YES	YES
Obs	434	403	434
R^2	0.305	0.839	0.482

6. Heterogeneity Analysis

6.1 Geographic heterogeneity

Due to regional economic imbalances in China, we split the sample into Eastern, Central, and Western regions (Table 9, Columns 1–3). The results show that the impact of DI is positive and significant across all regions, but follows a Central > Eastern > Western pattern. The Central region exhibits the largest coefficient (coef = 0.812), suggesting it benefits from a steep adoption curve and tech-catchup advantages. The Eastern region, having a more mature digital infrastructure, exhibits a slightly smaller coefficient (coef = 0.605), reflecting early signs of diminishing marginal returns. The Western region, constrained by digital infrastructure gaps, shows the smallest coefficient (coef = 0.456).

6.2 Level and sub-dimensional heterogeneity

We split the sample based on the median DI level. The coefficient of DI in high-DI regions ($\beta = 0.715$, $p < 0.01$) is larger than in low-DI regions ($\beta = 0.489$, $p < 0.01$), indicating positive network externalities. When analyzing the sub-dimensions of DI, we find that the coefficient for Intelligentization ($\beta = 0.412$, $p < 0.01$) is larger than that for Digitalization ($\beta = 0.284$, $p < 0.01$), indicating that advanced AI and automation applications yield greater resilience benefits than basic digitalization.

6.3 Agglomeration heterogeneity

We divide the sample by the median industrial agglomeration level (Table 9, Columns 4–5). The results show that the resilience-enhancing effect of DI is larger in regions with high industrial agglomeration ($\beta = 0.758$, $p < 0.01$) than in low-agglomeration regions ($\beta = 0.512$, $p < 0.01$), supporting the complementarity between physical spatial clusters and virtual digital networks.

Table 9: Heterogeneity Analysis Results

	(1) Eastern	(2) Central	(3) Western	(4) High Agglom.	(5) Low Agglom.
DI	0.605*	0.812*	0.456*	0.758*	0.512*
	(0.112)	(0.143)	(0.108)	(0.095)	(0.120)
Controls	YES	YES	YES	YES	YES
Province/Year FE	YES	YES	YES	YES	YES
Obs	154	112	168	217	217

7. Conclusions and policy implications

7.1 Conclusions

Using panel data from 31 Chinese provinces from 2011 to 2024, this paper evaluates the impact of Digital-Intelligence Integration (DI) on manufacturing industry chain resilience. Our findings demonstrate that DI significantly enhances manufacturing resilience, with the largest impact observed on the driving power dimension. These baseline findings remain robust to various specifications, including municipality exclusions, alternative measures, and 2SLS endogeneity checks. Mediation analysis reveals that DI enhances resilience through three main channels: promoting breakthrough innovation, improving the local business environment, and facilitating industrial agglomeration. Finally, heterogeneity analysis shows that the impact of DI is strongest in the Central region, high-DI regions, and areas characterized by high industrial agglomeration.

7.2 Policy implications

Based on these conclusions, we propose the following recommendations:

1. Strengthen Digital Infrastructure: Policymakers should accelerate 5G, industrial internet, and data center deployments, particularly in the Central and Western regions, to bridge the regional digital divide and expand the coverage of

digital-intelligence networks.

2. Support Smart Manufacturing Scenarios: Governments should provide targeted subsidies for SME cloud integration and encourage leading manufacturers to develop industrial internet platforms, transitioning digital applications from basic tools to advanced intelligent decision-making systems.

3. Foster Integrated Digital Ecosystems: Regional industrial plans should coordinate digital infrastructure investments with business environment optimization and financial inclusion, encouraging manufacturing firms to cluster in digitally integrated zones to unlock spatial synergies and network externalities.

4. Transition to Core Technology Innovation: Policies should support breakthrough innovation rather than incremental changes. Supporting R&D in basic industrial software, advanced sensors, and core AI algorithms will help reduce reliance on external technology providers, ensuring the long-term driving power of the manufacturing base.

8. Theoretical Extensions: Linking Resource Orchestration and Dynamic Capabilities to Industrial Policy

To translate these empirical findings into actionable management advice and policy tools, it is necessary to contextualize how resource orchestration and dynamic capabilities operate under government guidance. Neoclassical industrial economics often assumes that market mechanisms alone dictate technology diffusion. However, in emerging economies like China, industrial policy plays a critical role in structuring regional resource portfolios.

According to Resource Orchestration Theory, government intervention acts as an external orchestrator that:

Reduces Entry Barriers: Through subsidized public infrastructures (5G and cloud services), the state shapes the initial resource portfolio, allowing resource-constrained SMEs to engage in digitalization.

Coordinates Agglomeration: By planning smart manufacturing clusters and industrial zones, policies align physical spatial resources with virtual digital networks, promoting meso-level spatial orchestration.

From the Dynamic Capabilities perspective, these government interventions help firms build absorptive capacity (Cohen and Levinthal, 1990) and adaptive flexibility (Zhou and Wu, 2010). Under external environmental turbulence (such as the COVID-19 pandemic or trade sanctions), firms situated in highly orchestrated digital ecosystems can quickly reconfigure their supply chains because the infrastructure has already lowered the transaction costs of switching partners. Thus, public policy does not substitute for firm-level dynamic capabilities; instead, it establishes the resource platforms upon which these capabilities can be developed and leveraged.

Specifically, the deployment of industrial policies should focus on three levels of capability coordination:

At the micro-level, policies should encourage firms to upgrade from basic digitalization (structured assets) to advanced intelligent systems (bundled capabilities) by subsidizing AI integration, machine learning algorithms, and digital twin models.

At the meso-level, local governments must foster digital industrial clusters that align physical spatial agglomeration with virtual data integration. This spatial-digital synergy mitigates localized supply risks and expands the capacity margins of the regional network.

At the macro-level, the optimization of the business environment and digital financial inclusion must be prioritized to ease the credit constraints of smaller manufacturers, enabling them to invest in deep digital transformations and dynamically adjust under crisis conditions.

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Conflict of Interest

The authors declare that they have no conflicts of interest to this work.

References

Aslam, H., Rehman, A. U., Iftikhar, A., Haq, M. Z. U., Akbar, U., & Kamal, M. M. (2025). Digital transformation: Unlocking supply chain resilience through adaptability and innovation. *Technological Forecasting and Social Change, 219*, 124265.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120.

Barney, J. B. (2001). Is the resource-based "view" a useful perspective for strategic management research? Yes. *Academy of Management Review, 26*(1), 41–56.

Boschma, R. (2015). Towards an evolutionary perspective on regional resilience. *Regional Studies, 49*(5), 733–751.

Chen, Y., Li, B., & Huo, B. (2025). Building operational resilience through digitalization: The roles of supply chain network position. *Technological Forecasting and Social Change, 211*, 123846.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal, 21*(10-11), 1105–1121.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal, 17*(S2), 109–122.

Guo, J. (2025). How generative AI adoption affects supply chain resilience: An operations and supply chain management perspective. *Technological Forecasting and Social Change, 224*, 124446.

He, Z. C., Li, Y. J., & Wu, Y. (2024). Industrial Collaborative Agglomeration, Technological Innovation, and Manufacturing Industrial Chain Resilience. *Studies in Science of Science, 42*(03), 515-527.

Ivanov, D. (2023). Intelligent digital twin (iDT) for supply chain stress-testing, resilience, and viability. *International Journal of Production Economics, 263*, 108938.

Martin, R. (2012). Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography, 12*(1), 1–32.

Sirmon, D. G., Hitt, M. A., & Ireland, R. D. (2007). Managing firm resources in dynamic environments to create value: Looking at structuring, bundling, and leveraging capabilities. *Academy of Management Review, 32*(1), 273–292.

Sirmon, D. G., Hitt, M. A., Ireland, R. D., & Gilbert, B. A. (2011). Resource orchestration to create competitive advantage: Breadth, depth, and life cycle effects. *Journal of Management, 37*(5), 1390–1412.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533.

Wang, L., & Duan, L. (2025). Optimization of Business Environment, Supply Chain Finance, and Industrial Chain Resilience. *Finance Research Letters, 86*, 108867.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal, 5*(2), 171–180.

Zhou, K. Z., & Wu, F. (2010). Technological capability, dynamic capability, and organizational performance. *Journal of Business Research, 63*(3), 224–231.

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