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The Role of Digital Technologies in Enhancing Supply Chain Visibility and Resilience

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ABSTRACT

This study examines the mechanisms through which digital technology adoption enhances supply chain visibility and resilience. Grounded in information processing theory, the resource-based view, and the dynamic capabilities perspective, this study develops and empirically tests an integrated framework in which supply chain visibility mediates the relationship between digital technology adoption and supply chain resilience. Drawing on survey data from 742 manufacturing and logistics firms across 23 countries, this study employs hierarchical regression, structural equation modeling (SEM), and rigorous endogeneity controls including instrumental variables and propensity score matching. Findings confirm that digital technologies specifically IoT, blockchain, AI, big data analytics, and cloud computing exert a significant positive effect on supply chain visibility ($\beta = 0.412$, $p < .001$) and resilience ($\beta = 0.298$, $p < .001$). Supply chain visibility significantly predicts resilience ($\beta = 0.486$, $p < .001$) and mediates 67.4% of the total effect of digital technologies on resilience, confirmed by bootstrap confidence intervals [0.156, 0.253] and a Sobel test ($Z = 8.745$, $p < .001$). Heterogeneity analyses reveal stronger effects in high-complexity supply chains and technology-intensive industries. The findings contribute by integrating previously fragmented research streams and providing robust empirical evidence for the role of digitalization in building resilient supply chains. Practical implications support strategic digital investment with visibility as a key intermediate performance goal; policy implications highlight the need for infrastructure support and interoperability standards.

Keywords: Digital technologies; Supply chain visibility; Supply chain resilience; Blockchain; Internet of Things; Artificial intelligence; Big data analytics; Structural equation modeling

1. Introduction

Modern supply chains face unprecedented disruption from natural disasters, geopolitical tensions, and global pandemics, exposing fundamental vulnerabilities in conventional management approaches (Dubey et al., 2019; Ivanov & Dolgui, 2020). These shocks have accelerated organizational interest in digital transformation as a pathway to greater resilience (Sharma et al., 2020). Digital technologies such as blockchain, the Internet of Things (IoT), artificial intelligence (AI), big data analytics, and cloud computing are transforming supply chain visibility by enabling real-time information flows, predictive analytics, and enhanced coordination across complex networks (Koh et al., 2020; Lohmer & Lasch, 2020).

Despite growing scholarly attention, significant gaps remain in understanding the precise mechanisms through which digitalization contributes to enhanced visibility and resilience (Brusset & Teller, 2017; El Baz & Ruel, 2021). Three research streams address aspects of this phenomenon but exhibit critical limitations. First, studies of digital technology adoption predominantly focus on implementation challenges rather than performance outcomes (Wong et al., 2020; Kamble et al., 2020). Second, visibility research treats technology as peripheral rather than central to its theoretical development (Brandon-Jones et al., 2014). Third, while the resilience literature acknowledges the importance of information systems, it has not systematically theorized how specific technologies influence resilience outcomes (Pettit et al., 2019).

This study addresses these gaps by investigating the following research question: How do digital technologies improve supply chain visibility and resilience, and through what mechanisms? Specifically, this study examines:

(1) the direct effects of digital technology adoption on visibility and resilience,

(2) the mediating role of visibility in the digitalization–resilience relationship, and

(3) the moderating influence of organizational and environmental boundary conditions.

The contributions of this study are threefold. First, this study develops a theoretically grounded and empirically validated model that explicates the digitalization–visibility–resilience pathway. Second, this study advances methodological rigor by operationalizing digital technology adoption as a multi-dimensional construct. Third, this study identifies contextual factors that moderate technology effectiveness, offering insight applicable across diverse organizational and geographic settings.

2. Theoretical Framework and Hypothesis Development

2.1. Theoretical Foundations

Digital Technologies in Supply Chain Management

Digital technologies are advanced information and communication systems that enable organizations to capture, process, and distribute information across supply chains with unprecedented speed and accuracy (Büyüközkan & Göçer, 2018; Fosso Wamba et al., 2020). Blockchain provides distributed ledgers that ensure data integrity and transparency (Saberi et al., 2018). IoT enables real-time monitoring through connected sensors (Ben-Daya et al., 2019). AI facilitates pattern recognition and optimization to enhance predictive capabilities (Baryannis et al., 2018). Big data analytics transforms diverse data sources into actionable insights (Nguyen et al., 2018). Cloud computing provides scalable infrastructure for advanced analytical tools (Helo & Hao, 2017).

Supply Chain Visibility

Supply chain visibility denotes the extent to which supply chain actors have access to timely and accurate information regarding the status, location, and condition of products and materials across the network (Barratt & Oke, 2007; Brandon-Jones et al., 2014). From an information processing theory perspective (Galbraith, 1974), visibility addresses the information asymmetry that characterizes complex supply networks. Greater visibility reduces environmental uncertainty, thereby enabling proactive risk anticipation and response (Wieland & Durach, 2021).

Supply Chain Resilience

Supply chain resilience is the dynamic capability to anticipate, withstand, and recover from unforeseen disruptions while sustaining operational continuity (Ponomarov & Holcomb, 2009). Resilience encompasses four dimensions: anticipation, resistance, response/recovery, and adaptation (Ambulkar et al., 2015). The dynamic capabilities perspective (Teece et al., 1997) provides a theoretical foundation for understanding how organizations build resilience through capability-development activities, while the resource-based view (Barney, 1991; Wade & Hulland, 2004) positions digital technologies as valuable and rare resources that generate sustained competitive advantage.

2.2. Hypothesis Development

H1: Digital Technologies and Supply Chain Visibility

Digital technologies enhance visibility through multiple complementary mechanisms. IoT devices enable continuous real-time tracking of assets and inventory across supply chain nodes (Ben-Daya et al., 2019; Tao et al., 2018). Blockchain generates immutable transaction records that establish transparent audit trails throughout the supply network (Saberi et al., 2018; Queiroz & Wamba, 2019). Big data analytics integrates heterogeneous information into a unified operational picture (Nguyen et al., 2018; Dubey et al., 2019). AI-powered systems identify emerging risks and anomalies and generate automated alerts (Baryannis et al., 2018). Cloud computing provides centralized, accessible information repositories (Helo & Hao, 2017). Collectively, these technologies directly address the information asymmetry problems central to information processing theory (Galbraith, 1974). Accordingly:

H1: Digital technology adoption positively influences supply chain visibility.

H2: Supply Chain Visibility and Supply Chain Resilience

Supply chain visibility enables resilience through several reinforcing pathways. First, visibility enhances anticipation by generating early warning signals of potential disruptions (Brandon-Jones et al., 2014; Wieland & Durach, 2021). Second, visibility strengthens resistance by maintaining operational awareness during periods of disruption (Scholten & Schilder, 2015). Third, visibility accelerates response and recovery by providing accurate, timely post-disruption information (Ambulkar et al., 2015). Fourth, visibility facilitates adaptation by enabling organizational learning from disruption events (Scholten & Schilder, 2015). From an information processing perspective, visibility reduces informational equivocality in high-stakes decision-making contexts (Galbraith, 1974). Therefore:

H2: Supply chain visibility positively influences supply chain resilience.

H3: Digital Technologies and Supply Chain Resilience

Beyond their indirect effect through visibility, digital technologies also exert direct effects on resilience. AI-powered predictive analytics enables organizations to anticipate disruptions before they materialize (Baryannis et al., 2018; Ivanov, 2020). Digital technologies enhance operational flexibility and agility by accelerating situational analysis and facilitating rapid network reconfiguration (Lohmer & Lasch, 2020; Bag et al., 2021). Blockchain fosters inter-organizational trust and collaboration, thereby enabling collective resilience (Saberi et al., 2018; Cole et al., 2019). Cloud computing provides redundancy and elasticity in information processing infrastructure (Helo & Hao, 2017). Therefore:

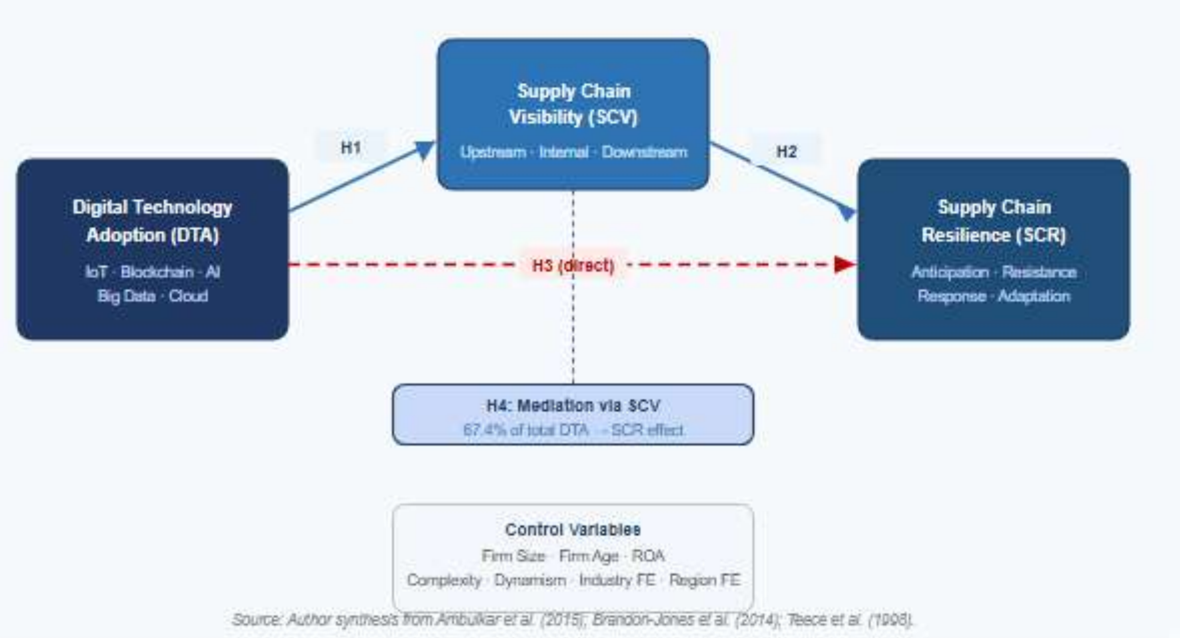
H3: Digital technology adoption positively influences supply chain resilience.

H4: Mediating Role of Supply Chain Visibility

Visibility constitutes a critical mechanism through which digital technologies translate into resilience outcomes. Specifically, digital technologies enhance information processing capability, which in turn increases supply chain visibility (Brandon-Jones et al., 2014), which subsequently enables specific resilience capabilities. This sequential process suggests that digital technologies alone are insufficient; organizations must leverage these technologies to achieve visibility, which ultimately drives resilience (El Baz & Ruel, 2021). Therefore:

H4: Supply chain visibility mediates the positive relationship between digital technology adoption and supply chain resilience.

Figure 1: Theoretical Framework and Research Hypotheses



Source: Author synthesis from Ambulkar et al. (2015); Brandon-Jones et al. (2014); Teece et al. (1998).

Figure 1. Theoretical framework. Solid arrows represent the mediated pathway (H1, H2); the dashed arrow represents the direct effect (H3). H4: Mediation via SCV. Controls: Firm Size, Age, ROA, Complexity, Dynamism, Industry FE, Region FE. See fig1.svg.

3. Research Methodology

3.1. Research Design and Sampling Frame

This study employs a cross-sectional survey design targeting manufacturing and logistics firms across multiple national contexts. The sampling frame was constructed from the Dun & Bradstreet Global Business Directory and regional industry association membership lists, ensuring representation across firm sizes, industries, and geographic regions. Purposive sampling was applied to target senior supply chain executives and operations managers with decision-making authority a criterion aligned with key-informant methodology (Podsakoff et al., 2003).

Data collection was conducted between January 2023 and June 2024 using structured questionnaires administered via Qualtrics. Initial contact letters were sent to 2,847 eligible firms; 856 responses were received (response rate: 30.1%). After excluding 114 responses due to missing data (>10%) or failed attention checks, the final analytical sample comprised 742 valid observations from 23 countries (Asia-Pacific: 168; Europe: 221; North America: 278; Emerging markets: 75). To assess non-response bias, early and late respondents were compared on key firm characteristics (size, age, industry) following Armstrong and Overton (1977); no significant differences were detected (all p > .10), indicating non-response bias is unlikely to threaten the validity of findings.

Common method bias was mitigated through procedural remedies including anonymity assurances, counterbalancing item order, separating predictor and criterion items, and embedding attention-check items (Podsakoff et al., 2003). Secondary financial data (ROA) were obtained from Orbis and Compustat to supplement self-reported measures, providing methodological triangulation. Harman's single-factor test yielded a maximum single-factor variance of 38.2%, below the conventional 50% threshold, indicating that common method variance is unlikely to be a critical threat.

3.2. Measures

Digital Technology Adoption (DTA)

DTA was operationalized as a second-order reflective–reflective construct comprising 20 items across five dimensions IoT (4 items), blockchain (4 items), AI/machine learning (4 items), big data analytics (4 items), and cloud computing (4 items) adapted from Queiroz et al. (2019) and Bag et al. (2021). Items were measured on seven-point Likert scales (1 = not at all adopted, 7 = fully adopted). Overall Cronbach's α = 0.91; composite reliability (CR) = 0.93; average variance extracted (AVE) = 0.62.

Supply Chain Visibility (SCV)

SCV was measured using a 12-item scale adapted from Brandon-Jones et al. (2014) and Barratt and Oke (2007), capturing three dimensions: upstream visibility (4 items), internal visibility (4 items), and downstream visibility (4 items). Items employed seven-point Likert scales (1 = strongly disagree, 7 = strongly agree). Cronbach's α = 0.89; CR = 0.91; AVE = 0.67.

Supply Chain Resilience (SCR)

SCR was operationalized as a multidimensional construct comprising 16 items across four dimensions anticipation, resistance, response/recovery, and adaptation adapted from Ambulkar et al. (2015) and Pettit et al. (2019). Seven-point Likert scales were employed. Cronbach's α = 0.94; CR = 0.95; AVE = 0.71. As a robustness check, an objective resilience measure (coefficient of variation of three-year revenue performance) was also computed.

Control Variables

Firm Size (natural log of number of employees), Firm Age (years since establishment), ROA (net income/total assets), Supply Chain Complexity (composite measure of number of suppliers, customers, geographic dispersion, and product variety; Bode & Wagner, 2015), and Environmental Dynamism (four-item scale; α = 0.83) were included as controls. Industry and region fixed effects were incorporated in all models.

3.3. Analytical Strategy

Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) was conducted in R using the lavaan package (Rosseel, 2012) prior to hypothesis testing to evaluate the psychometric properties of the measurement model. Model fit was assessed using CFI, TLI, RMSEA, and SRMR in accordance with the guidelines of Hu and Bentler (1999). Discriminant validity was evaluated by comparing the square root of each construct's AVE with inter-construct correlations (Fornell & Larcker, 1981).

Structural Equation Modeling and Regression

Structural equation modeling (SEM) and hierarchical ordinary least squares (OLS) regression were used to test H1–H4. Mediation analysis followed the procedures recommended by Preacher and Hayes (2008), using bootstrapped confidence intervals based on 5,000 replications. Standard errors were clustered at the industry level to account for within-industry dependence. Endogeneity was addressed through three approaches: (1) instrumental variables (IV) estimation using industry-average digital technology adoption rates as instruments (relevance confirmed: first-stage F = 196.34, p < .001), (2) lagged independent variables, and (3) propensity score matching (PSM) to reduce selection bias.

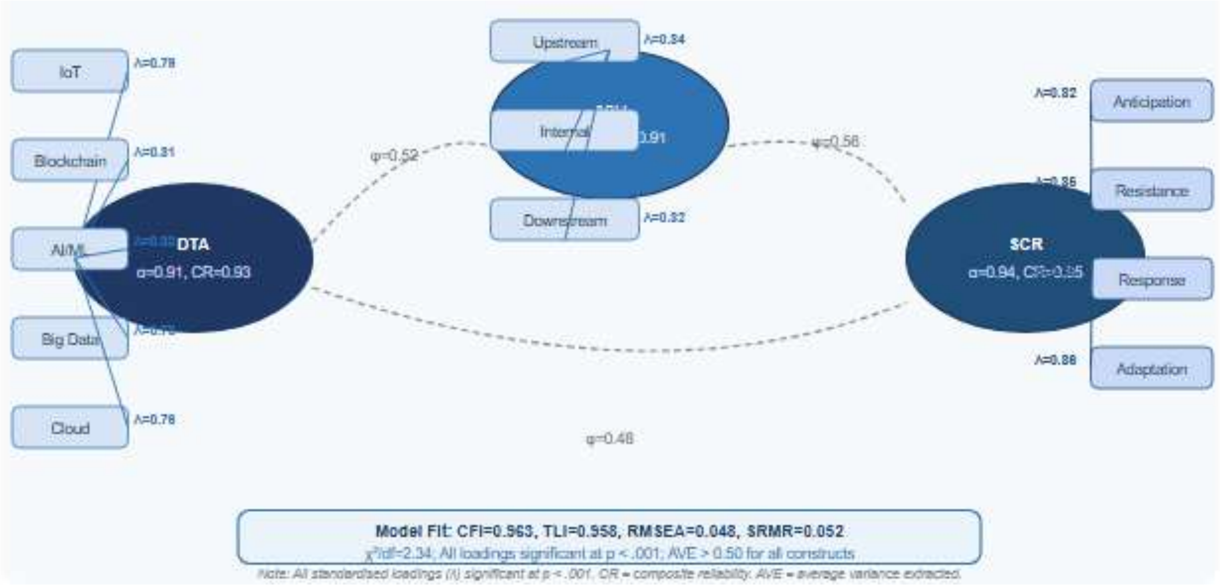
Table 1. Measurement Model: CFA Results, Reliability, and Validity Statistics

Construct / Indicator	Items (n)	α	CR	AVE	Factor Loadings Range	Discriminant Validity (√AVE)
Digital Tech. Adoption (DTA)	20	0.91	0.93	0.62	0.76–0.83	0.787
Supply Chain Visibility (SCV)	12	0.89	0.91	0.67	0.82–0.87	0.819
Supply Chain Resilience (SCR)	16	0.94	0.95	0.71	0.82–0.88	0.843

Construct / Indicator	Items (n)	α	CR	AVE	Factor Loadings Range	Discriminant Validity (√AVE)
Environmental Dynamism	4	0.83	0.86	0.61	0.74–0.82	0.781
Model Fit Indices: $\chi^2/df = 2.34$; CFI = 0.963; TLI = 0.958; RMSEA = 0.048 [90% CI: 0.038, 0.056]; SRMR = 0.052. All factor loadings significant at $p < .001$. Discriminant validity confirmed: all √AVE values exceed inter-construct correlations.						

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted; √AVE = square root of AVE. Discriminant validity confirmed: √AVE > all inter-construct correlations. Model fit: CFI = 0.963, TLI = 0.958, RMSEA = 0.048, SRMR = 0.052.

Figure 2: CFA Measurement Model Standardised Factor Loadings



4. Results

4.1. Descriptive Statistics and Preliminary Analysis

Table 2 presents means, standard deviations, and zero-order correlations for all study variables. Digital technology adoption exhibited a mean of 4.28 (SD = 1.45), supply chain visibility of 4.67 (SD = 1.23), and supply chain resilience of 4.89 (SD = 1.18), indicating moderate adoption levels with substantial variance across firms. All correlations among the focal constructs were positive and statistically significant (DTA–SCV: $r = .524$; DTA–SCR: $r = .478$; SCV–SCR: $r = .562$; all $p < .001$). Variance inflation factor (VIF) analysis confirmed the absence of multicollinearity concerns (mean VIF = 1.56; maximum VIF = 2.34, well below the commonly accepted threshold of 10).

Table 2. Descriptive Statistics and Bivariate Correlations

Variable	M	SD	1	2	3	4	5	6	7
1. DTA	4.28	1.45							
2. SCV	4.67	1.23	.524***						
3. SCR	4.89	1.18	.478***	.562***					
4. Size (ln)	7.52	1.87	.287***	.213***	.198***				
5. Age (yrs)	34.60	26.40	.104**	.089*	.112**	.345***			
6. ROA	0.08	0.09	.156***	.187***	.221***	.078*	.034		
7. Complexity	4.35	1.52	.298***	.341***	.289***	.412***	.156***	.067	
8. Dynamism	4.71	1.34	.189***	.178***	.224***	.045	−.023	.091*	.187***

Note. N = 742. M = mean; SD = standard deviation. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

4.2. Main Regression Results

Table 3 reports hierarchical OLS regression results testing H1–H3. Models 1 and 2 use supply chain visibility (SCV) as the dependent variable; Models 3–6 use supply chain resilience (SCR). The inclusion of control variables in all baseline models (Models 1, 3, 5) establishes the baseline explained variance.

Support for H1: Model 2 demonstrates that digital technology adoption is a significant positive predictor of supply chain visibility ($\beta = 0.412$, $p < .001$), explaining an additional 20.4% of variance beyond controls ($\Delta R^2 = 0.204$).

Support for H2: Model 4 demonstrates that supply chain visibility is a strong positive predictor of supply chain resilience ($\beta = 0.486$, $p < .001$), explaining an additional 25.8% of variance ($\Delta R^2 = 0.258$).

Support for H3: Model 6 demonstrates that digital technology adoption positively and significantly predicts resilience ($\beta = 0.298$, $p < .001$), explaining an additional 17.9% of variance ($\Delta R^2 = 0.179$).

Table 3. Hierarchical OLS Regression Results (H1–H3)

Variable	Model 1 (SCV)	Model 2 (SCV)	Model 3 (SCR)	Model 4 (SCR)	Model 5 (SCR)	Model 6 (SCR)
DTA		0.412***				0.298***
		(0.038)				(0.041)
SCV				0.486***		
				(0.045)		
Firm Size	0.087**	0.034	0.076*	0.024	0.098**	0.062*
Firm Age	0.002*	0.001	0.003**	0.002*	0.003**	0.002*
ROA	0.789***	0.621***	0.934***	0.687***	0.856***	0.713***
Complexity	0.198***	0.089**	0.156***	0.067*	0.187***	0.098**
Dynamism	0.091**	0.042	0.124***	0.079**	0.134***	0.095**
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.248	0.452	0.231	0.489	0.219	0.398
ΔR^2		0.204		0.258		0.179
N	742	742	742	742	742	742
Note. Standard errors in parentheses. ***p < .001; **p < .01; *p < .05. Industry and region fixed effects included in all models. N = 742.						

Note. Standardized coefficients. Standard errors in parentheses. ***p < .001; **p < .01; *p < .05. All models include industry and region fixed effects. N = 742.

4.3. Mediation Analysis (H4)

Table 4 presents the mediation analysis results testing H4. Following Preacher and Hayes (2008), three-step mediation modeling was conducted.

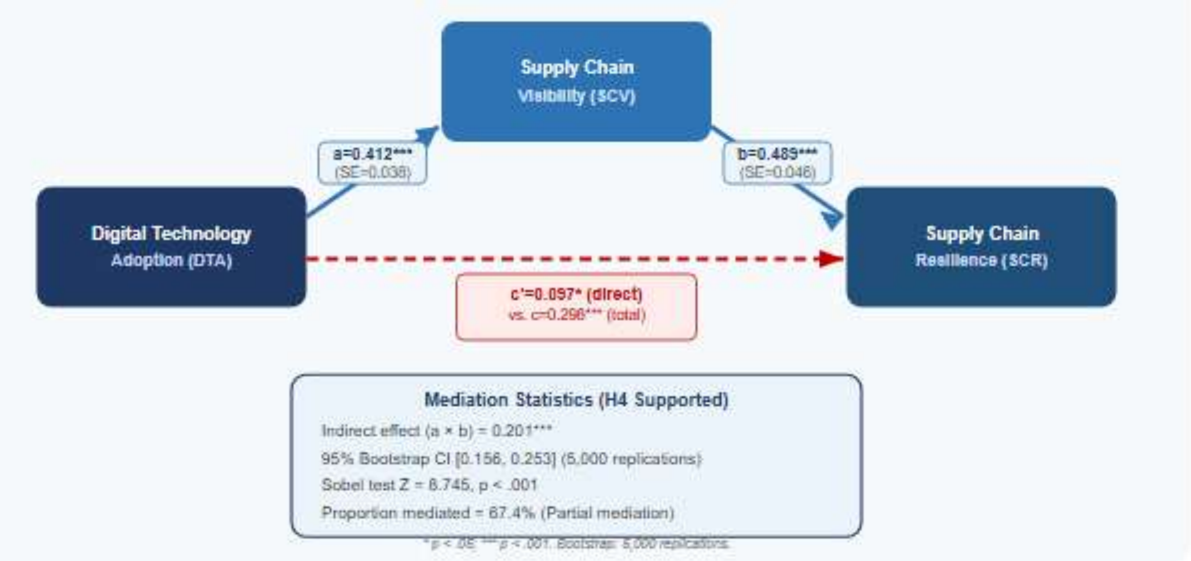
Support for H4: The inclusion of supply chain visibility as a mediator substantially attenuates the effect of digital technology adoption on resilience, from β = 0.298 (p< .001, Step 2) to β = 0.097 (p< .05, Step 3). The indirect effect (a × b) is 0.201 (95% bootstrap CI: [0.156, 0.253]; Sobel Z = 8.745, p< .001), representing 67.4% of the total effect. The persistence of a significant direct effect (β = 0.097, p< .05) confirms partial, rather than full, mediation, indicating that visibility is the primary but not the exclusive mechanism linking digital technologies to resilience.

Table 4. Mediation Analysis: Supply Chain Visibility as Mediator (H4)

Variable	Step 1 (SCV)	Step 2 (SCR)	Step 3 (SCR)
DTA	0.412*** (0.038)	0.298*** (0.041)	0.097* (0.042)
SCV			0.489*** (0.046)
Controls / FEs	Included	Included	Included
R^2	0.452	0.398	0.524
Mediation Statistics			
Total effect (c)			0.298***
Direct effect (c')			0.097*
Indirect effect (a × b)			0.201***
Proportion mediated			67.4%
Sobel test (Z)			8.745***
Bootstrap 95% CI (5,000 reps)			[0.156, 0.253]
Note. Standard errors in parentheses. ***p < .001; *p < .05. Partial mediation confirmed: direct effect remains significant. N = 742.			

Note. Standard errors in parentheses. All models include control variables, industry and region FEs. ***p < .001; *p < .05. Bootstrap based on 5,000 replications. N = 742.

Figure 3: Mediation Analysis Path Diagram DTA → SCV → SCR



4.4. Robustness Checks

Table 5 reports six robustness tests to rule out alternative explanations. The IV first-stage F-statistic of 196.34 ($p < .001$) confirms instrument relevance; the second-stage coefficient ($\beta = 0.314$, $p < .001$) validates H3 under exogenous variation. Lagged DTA models ($\beta = 0.276$, $p < .001$) and PSM-matched samples ($\beta = 0.291$, $p < .001$) replicate the primary findings. Alternative operationalizations technology capital expenditure as a DTA proxy ($\beta = 0.421$, $p < .001$) and coefficient of variation as an objective SCR proxy further corroborate the robustness of results across measurement and sampling specifications.

Table 5. Robustness Tests: Endogeneity Controls and Alternative Measures

Variable	IV Stage 1 (DTA)	IV Stage 2 (SCR)	Lagged DTA (SCR)	PSM Sample (SCR)	Alt. DTA (SCR)	Alt. SCR (CV)
Industry avg. DTA	0.728***					
DTA		0.314***	0.276***	0.291***		−0.038***
DTA_invest					0.421***	
SCV		0.467***	0.501***	0.478***	0.476***	−0.054***
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	742	742	687	584	718	742

Variable	IV Stage 1 (DTA)	IV Stage 2 (SCR)	Lagged DTA (SCR)	PSM Sample (SCR)	Alt. DTA (SCR)	Alt. SCR (CV)
R^2	0.618	0.496	0.537	0.518	0.511	0.387
F-stat (1st stage)	196.34***					
Note. Standard errors clustered at industry level. CV = coefficient of variation (objective resilience proxy). PSM = propensity score matching. Alt. DTA = technology capital expenditure (% total capex). ***p < .001; **p < .01; *p < .05.						

Note. Standard errors clustered at industry level. ***p < .001; **p < .01; *p < .05. CV = coefficient of variation (objective resilience proxy). PSM = propensity score matching.

4.5. Heterogeneity Analysis

Table 6 reports cross-group heterogeneity analyses examining boundary conditions. Panel A presents DTA → SCR coefficients and Panel B presents SCV → SCR coefficients across industry type, supply chain complexity, firm size, and geographic region.

Digital technology effects on resilience are significantly stronger in technology-intensive industries (β = 0.124 vs. 0.089, $\chi^2(1) = 3.87$, p = .049) and high-complexity supply chains (β = 0.145 vs. 0.067, $\chi^2(1) = 4.23$, p = .040), consistent with the contingency logic that the value of digital investments is amplified when information processing demands are high (Bode & Wagner, 2015). Regional analyses indicate significant effects in North America (β = 0.098), Europe (β = 0.115), and Asia-Pacific (β = 0.134), but non-significant effects in emerging markets (β = 0.076, p > .05), consistent with infrastructure and complementary capability constraints in less digitally developed contexts (Kumar et al., 2020). Critically, the SCV → SCR relationship is statistically significant across all subgroups (β range: 0.423–0.534, all p < .001; Panel B), demonstrating the universal role of visibility in building resilience irrespective of organizational or geographic context.

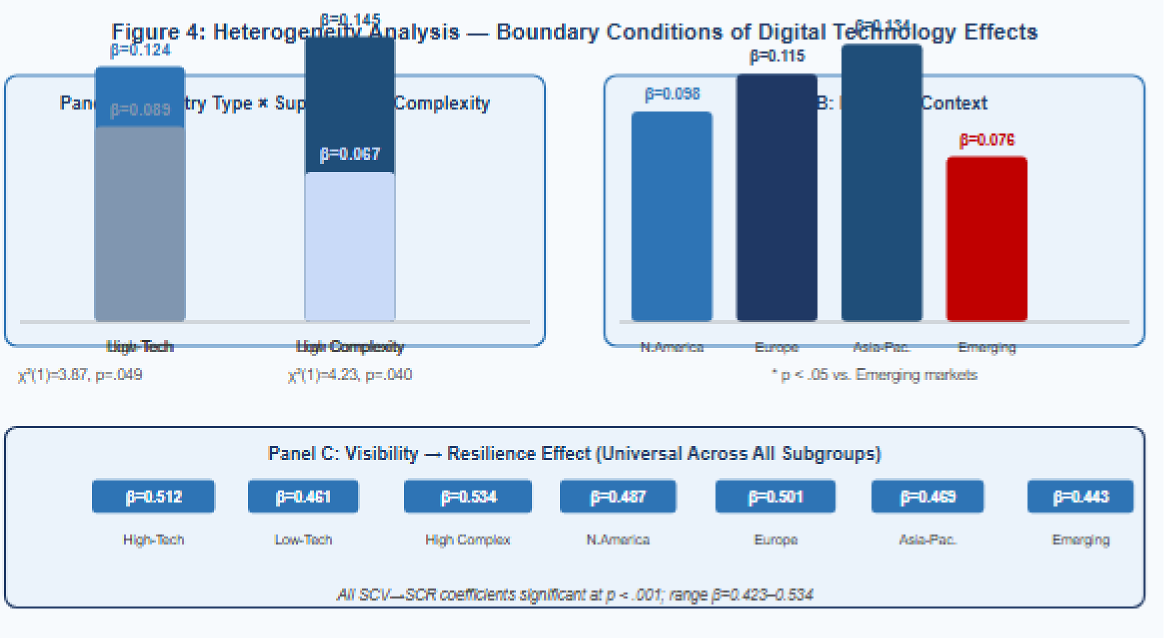
Table 6. Heterogeneity Analysis: Boundary Conditions of Digital Technology Effects

Variable	High-Tech (n=421)	Low-Tech (n=321)	High Complexity (n=398)	Low Complexity (n=344)	Large Firms (n=412)	SMEs (n=330)	Developed (n=667)	Emerging (n=75)
Panel A: DTA → SCR coefficients								
DTA	0.124** (0.048)	0.089* (0.052)	0.145*** (0.046)	0.067 (0.059)	0.112** (0.051)	0.087* (0.048)	0.112** (0.049)	0.076 (0.062)
R^2	0.548	0.487	0.571	0.452	0.534	0.512	0.531	0.468
Panel B: SCV → SCR coefficients								
SCV	0.512*** (0.056)	0.461*** (0.067)	0.534*** (0.052)	0.423*** (0.071)	0.467*** (0.058)	0.506*** (0.062)	0.487*** (0.059)	0.443*** (0.074)
R^2	0.571	0.503	0.589	0.464	0.551	0.529	0.548	0.481

Note. Standard errors in parentheses. ***p < .001; **p < .01; *p < .05. All models include controls, industry and region FE. Cross-group difference tests: High-Tech vs Low-Tech $\chi^2(1)=3.87$, p=.049; High vs Low Complexity $\chi^2(1)=4.23$, p=.040. Developed = N. America + Europe + Asia-Pacific.

Note. Standard errors in parentheses. ***p < .001; **p < .01; *p < .05. All models include controls, industry and region FEs. $\chi^2(1)$ = cross-group Wald tests for coefficient equality. Developed markets = N. America + Europe + Asia-Pacific (n = 667).

Figure 4: Heterogeneity Analysis   Boundary Conditions of Digital Technology Effects



5. Discussion

This study provides robust evidence that digital technology adoption significantly enhances both supply chain visibility and resilience, with supply chain visibility mediating approximately 67.4% of the total digitalization–resilience effect. This finding aligns with the conceptualization of digital technologies as transformative information-processing enablers that resolve the information asymmetry inherent in complex supply networks (Fosso Wamba et al., 2020; Galbraith, 1974). The strong visibility–resilience relationship (β = 0.486) corroborates information processing theory by demonstrating that visibility supports each of the four resilience dimensions anticipation, resistance, response, and adaptation (Ambulkar et al., 2015).

The persistence of a significant direct effect (β = 0.097) suggests that visibility is not the sole mechanism sustaining resilience. Additional pathways may include predictive analytics capabilities, operational flexibility, and inter-organizational collaborative mechanisms enabled by digital technologies (Baryannis et al., 2018; Lohmer & Lasch, 2020). From a resource-based perspective, digital technologies function as strategic resources that generate competitive advantage through dynamic capability development (Barney, 1991; Teece et al., 1997; Wade & Hulland, 2004).

Heterogeneity analyses reveal important boundary conditions. Digital technologies deliver greater resilience benefits in high-complexity supply chains, reflecting the contingency principle that information-processing investments are most valuable when information demands are greatest (Bode & Wagner, 2015). Weaker effects in emerging markets underscore the importance of complementary digital infrastructure and organizational capabilities (Kumar et al., 2020). The universality of the visibility–resilience relationship, however, suggests that visibility is a robust, context-invariant prerequisite for resilience a finding with important implications for both theory and managerial practice.

6. Implications, Limitations, and Conclusion

6.1. Theoretical Contributions

This study makes four theoretical contributions. First, it develops an integrated framework that connects digital technology adoption to supply chain resilience through the mediating mechanism of visibility, synthesizing information processing theory, the resource-based view, and dynamic capabilities into a unified explanatory model. Second, it establishes the critical mediating role of visibility through rigorous endogeneity-controlled testing, resolving prior theoretical ambiguity regarding whether visibility constitutes a mechanism or an outcome of digitalization. Third, it provides robust multi-country, multi-industry evidence that digital technologies and visibility are primary antecedents of supply chain resilience. Fourth, it identifies important boundary conditions through heterogeneity analyses, specifying when and where digital technologies deliver the greatest resilience benefits (Tukamuhabwa et al., 2015; El Baz & Ruel, 2021).

6.2. Managerial Implications

The findings carry five practical implications for supply chain practitioners. First, organizations should conceptualize digital investments as strategic resilience enablers rather than operational efficiencies, employing a portfolio approach across complementary technologies. Second, supply chain visibility should be established as an explicit intermediate performance milestone in digital transformation roadmaps. Third, digital investment strategies should be calibrated to supply chain characteristics: complex supply chains warrant comprehensive, multi-technology investments, whereas simpler chains may benefit from selective, targeted adoption. Fourth, organizations should invest in complementary organizational capabilities including workforce training, cross-functional integration, and change management to maximize the resilience returns from digital investments. Fifth, digital initiatives should be explicitly mapped to the four resilience dimensions: anticipation, resistance, response, and adaptation.

6.3. Policy Implications

Policymakers should:

(1) invest in digital infrastructure including broadband connectivity, cloud ecosystems, and digital workforce skills development;

(2) develop sector-specific support programs that reflect heterogeneous technological and operational requirements;

(3) implement SME-oriented adoption facilitation programs, including subsidized consulting and grant mechanisms; and

(4) advance interoperability frameworks and data governance standards that enable secure inter-organizational information sharing while protecting proprietary information.

6.4. Limitations and Future Research Directions

Several limitations warrant acknowledgement. The cross-sectional design limits causal inference despite endogeneity controls; longitudinal designs would strengthen causal identification. The sample is restricted to manufacturing and logistics firms, potentially constraining generalizability to service-intensive supply chains. Measures of resilience and visibility rely on perceptual scales, albeit validated ones; objective longitudinal performance data would complement these findings. Analysis is conducted at the firm level, whereas resilience is inherently a network-level phenomenon.

Future research should: employ longitudinal designs to trace the temporal dynamics of digital transformation effects; conduct fine-grained analyses of individual technologies and their differential effects; examine process-level mechanisms linking visibility dimensions to specific resilience capabilities; extend analysis to network-level supply chain resilience; investigate implementation processes and change management challenges; examine emerging technologies including generative AI, digital twins, and autonomous systems; and integrate sustainability and behavioral perspectives into the human–technology interaction literature.

6.5. Conclusion

This study provides compelling evidence that digital technologies significantly enhance supply chain visibility and resilience, with visibility mediating approximately two-thirds of the total digitalization–resilience effect. Evidence from 742 firms across 23 countries confirms that IoT, blockchain, AI, big data analytics, and cloud computing enhance visibility by enabling real-time monitoring, transparent record-keeping, comprehensive data integration, and anomaly detection. Enhanced visibility subsequently builds resilience by strengthening anticipation, resistance, response, and adaptation capabilities.

Direct effects of digital technologies on resilience additionally operate through predictive analytics, operational flexibility, and collaborative capabilities. These relationships are conditioned by supply chain complexity, industry technology intensity, firm size, and geographic context, with benefits amplified in complex, technology-intensive supply chains and in developed economies. Theoretically, this study integrates information processing theory, the resource-based view, and dynamic capabilities into a coherent explanatory framework. For practitioners, findings endorse strategic digital investment and establish visibility as a critical intermediate performance objective. For policymakers, the results highlight the necessity of infrastructure investment, industry-specific support, and interoperability standards to enable digital transformation and supply chain resilience in an increasingly volatile global environment.

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