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DIGITAL TRANSFORMATION IMPACT ON SUPPLY CHAIN RESILIENCE

Taras Mukha
PhD Student, Kharkiv National Automobile and Highway University, Kharkiv, Ukraine;
e-mail: hammers.plant@gmail.com
ORCID: 0009-0008-9282-6833
(Corresponding author)

Nadiia Popova
D.Sc. in Economics, Corresponding Member, Professor of the Department of Management, Kharkiv National Automobile and Highway University,
ORCID: 0000-0003-2797-6989

ABSTRACT

This study investigates mechanisms through which logistics digital transformation influences supply chain resilience, testing hypotheses that transparency, integration, and capacity serve as parallel mediating pathways. The research addresses the gap in understanding how digital investments translate into resilient outcomes through distinct transmission mechanisms.

A cross-sectional survey collected data from 287 supply chain professionals in the manufacturing and distribution sectors. Sample size was justified through power analysis (G*Power: $\alpha = 0.05$, power = 0.80, $f^2 = 0.15$, minimum n = 138). Partial least squares structural equation modeling was conducted using SmartPLS 4.0 with a confirmatory approach. Bootstrap procedure employed 5,000 subsamples for bias-corrected confidence intervals. All constructs used validated multi-item scales measured on a seven-point Likert format.

The model explained 58.3% of the variance in supply chain resilience ($R^2 = 0.583$) with confirmed predictive relevance ($Q^2 = 0.402$). Digital transformation significantly influenced all mediators: transparency ($\beta = 0.412$, $p < 0.001$), integration ($\beta = 0.523$, $p < 0.001$), and capacity ($\beta = 0.467$, $p < 0.001$). Total effect on resilience ($\beta = 0.687$, 95% CI [0.593, 0.781]) substantially exceeded direct effect ($\beta = 0.190$). Integration demonstrated the strongest mediation ($f^2 = 0.35$), followed by transparency ($f^2 = 0.29$) and capacity ($f^2 = 0.18$). Approximately 72% of the total effect operated through mediated pathways (VAF = 72.3%). All ten hypotheses were supported.

Findings reveal that technology adoption alone captures only 27.7% of potential resilience benefits; deliberate capability development across transparency, integration, and capacity dimensions is essential. The mathematical predictive model enables quantitative estimation of resilience improvements from digital investments, supporting evidence-based resource allocation. Future research should employ longitudinal designs to establish temporal ordering and examine boundary conditions.

Keywords: digital transformation, supply chain resilience, partial least squares structural equation modeling, supply chain transparency, supply chain integration, supply chain capacity, mediation analysis, logistics digitalization

JEL Classification: L81, L91, M11, O33, Q55

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INTRODUCTION

Contemporary supply chains operate within increasingly volatile, uncertain, complex, and ambiguous environments, demanding unprecedented adaptive capabilities from organizations across all industrial sectors. The COVID-19 pandemic, escalating geopolitical tensions, climate-related disruptions, and rapid technological change have exposed critical vulnerabilities in traditional supply chain configurations, elevating resilience from operational consideration to strategic imperative requiring executive attention and substantial resource commitment (Echefaj et al., 2025). The frequency and severity of supply chain disruptions have increased dramatically over the past decade, with studies suggesting that major disruptions now occur with an annual probability exceeding 80% for global supply networks, creating substantial risks to organizational performance and stakeholder value delivery.

Within this challenging operational context, digital transformation has emerged as a potentially transformative force capable of fundamentally reshaping how organizations sense environmental changes, respond to operational disruptions, and recover from supply chain breakdowns across multiple dimensions simultaneously. Digital transformation in logistics encompasses strategic adoption of digital technologies and data-driven processes to fundamentally alter how supply chain activities are performed, coordinated, and optimized across organizational boundaries (Liu & Chiu, 2021). Unlike incremental automation initiatives focused on efficiency gains within existing processes, digital transformation represents holistic organizational change affecting business models, operational processes, customer relationships, and stakeholder interactions simultaneously.

Empirical evidence increasingly suggests that digitalized supply chains demonstrate enhanced resilience capabilities across anticipatory, responsive, and restorative dimensions. However, the mechanisms through which this relationship operates remain insufficiently understood in academic literature, limiting both theoretical advancement and practical application. Existing studies have established direct relationships between supply chain digitalization and resilience outcomes, with effect sizes ranging from $\beta = 0.397$ to $\beta = 0.908$ across various industrial contexts and geographic regions (Zhao et al., 2023; Sharma et al., 2024). However, treating this relationship as a direct linkage obscures intermediate mechanisms through which digital capabilities translate into resilient outcomes, preventing organizations from optimizing their digital investment strategies.

Recent scholarship calls for unpacking this conceptual black box through rigorous mediation analysis, identifying specific pathways and their relative contributions to overall resilience enhancement (Wang et al., 2024). Understanding these mechanisms holds both theoretical significance for advancing supply chain resilience theory and practical importance for guiding organizational digital investment decisions in resource-constrained environments where prioritization is essential. This study proposes and tests a parallel mediation model (Figure 1), positioning supply chain transparency, integration, and capacity as intervening mechanisms linking digital transformation to resilience outcomes.

This article addresses identified research gaps by developing and empirically testing a comprehensive mediation model. The study contributes to the literature by quantifying the relative importance of different mediation pathways, enabling organizations to understand not only whether digital transformation enhances resilience, but also how and through which specific mechanisms this enhancement occurs. Additionally, we develop a mathematical predictive model enabling practitioners to estimate resilience improvements from digital investments with quantitative precision. The remainder of this article proceeds as follows: Section 2 presents a comprehensive literature review, Section 3 articulates the research aim and objectives with hypothesis development, Section 4 details the methodological approach, Section 5 presents empirical results, Section 6 provides discussion, and Section 7 concludes with implications.

LITERATURE REVIEW

Theoretical Foundations

This study integrates three complementary theoretical perspectives to explain the mechanisms through which digital transformation influences supply chain resilience outcomes. Each theoretical lens captures distinct aspects of the digitalization-resilience relationship, and their integration enables a more comprehensive understanding than any single theory could provide independently.

Dynamic Capabilities Theory provides an overarching framework for understanding how organizations develop, deploy, and reconfigure resources in response to environmental change. Contemporary applications distinguish between sensing capabilities for identifying opportunities and threats, seizing capabilities for mobilizing resources effectively, and reconfiguring capabilities for continuous renewal and transformation (Kump et al., 2024). Applied to the supply chain resilience context, these capabilities map onto absorptive, response, and recovery dimensions respectively, providing a theoretical foundation for understanding how digital transformation enhances organizational ability to anticipate disruptions, respond effectively when they occur, and recover rapidly afterward (Zhao et al., 2023).

The Resource-Based View complements dynamic capabilities by explicating characteristics enabling resources to generate sustainable competitive advantage. Resources must satisfy VRIO criteria — valuable, rare, inimitable, and organizationally embedded — to confer lasting advantage (Jing & Fan, 2024). Digital transformation investments satisfying these criteria create inimitable supply chain capabilities that competitors cannot easily replicate. Jing and Fan (2024) demonstrate empirically that digital transformation serves as a strategic resource conferring competitive advantage through enhanced information processing and coordination capabilities.

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Information Processing Theory provides a specific explanation for how digital technologies enhance organizational capabilities under uncertainty. Organizations face information processing requirements arising from task uncertainty and interdependence, and must develop commensurate information processing capabilities to maintain effectiveness (Shamim et al., 2022). Digital transformation directly enhances information acquisition speed, processing accuracy, and cross-boundary dissemination capabilities, enabling organizations to manage greater complexity. Tiwari et al. (2024) demonstrate that supply chain visibility serves as a foundational information processing capacity upon which advanced digital capabilities depend.

Table 1. Theoretical foundations of digital transformation-resilience mechanisms. *(Source: compiled by authors based on theoretical literature synthesis)*

Theory	Core Tenets	Application to DT-SCR	Key Constructs
Dynamic Capabilities (Kump et al., 2024)	Sensing, seizing, and reconfiguring capabilities enable organizational adaptation to environmental change	DT enhances sensing through real-time monitoring, seizing via rapid resource mobilization, and reconfiguring through flexibility	Supply chain capacity, integration, resilience
Resource-Based View (Jing & Fan, 2024)	VRIO criteria: valuable, rare, inimitable, organized resources create sustainable competitive advantage	Digital capabilities as strategic resources creating firm-specific inimitability through complex integration	Digital transformation, data-driven decisions
Information Processing (Shamim et al., 2022)	Information processing requirements must match organizational capabilities under uncertainty	DT enhances information acquisition, processing accuracy, and cross-boundary dissemination	Transparency, visibility, information sharing

Digital Transformation and Supply Chain Resilience

Supply chain resilience refers to adaptive capability to prepare for unexpected disruptions, respond effectively to operational disturbances, and recover rapidly while maintaining continuous operations and stakeholder value delivery (Dubey et al., 2021). This comprehensive conceptualization encompasses proactive dimensions, including anticipation and preparation, reactive dimensions involving rapid response and adaptation, and restorative dimensions addressing recovery and organizational learning. Digital transformation contributes to each dimension through distinct yet interconnected mechanisms.

Empirical evidence consistently supports a positive relationship between digital transformation and supply chain resilience. Zhao et al. (2023) found that supply chain digitalization significantly enhances absorptive capability ($\beta = 0.408$), response capability ($\beta = 0.397$), and recovery capability ($\beta = 0.428$) in manufacturing firms. Sharma et al. (2024) demonstrated exceptionally strong effects in smart supply chain contexts, with resilience coefficients reaching $\beta = 0.908$. Bianco et al. (2024) confirmed that digitalization positively influences resilience even during severe disruptions such as the COVID-19 pandemic, providing evidence that digital capabilities maintain effectiveness precisely when most needed.

Cloud-based systems and Software-as-a-Service solutions provide scalable infrastructure that can be rapidly adjusted to changing operational requirements (Mukha, 2025). Mukha and Popova (2025) further emphasize how SaaS adoption in logistics management enables real-time information sharing across organizational boundaries, facilitating coordinated response during disruptions and creating conditions for enhanced transparency, integration, and capacity development.

Mediating Mechanisms: Transparency, Integration, and Capacity

Supply chain transparency refers to the extent to which stakeholders have shared access to accurate, timely, and actionable information across the supply network (Wang et al., 2024). Digital transformation enables transparency through shared information environments, digital tracking systems, and standardized data exchange protocols. Tiwari et al. (2024) emphasize that supply chain visibility serves as a foundational resource upon which advanced digital capabilities depend, creating information infrastructure essential for coordinated resilience responses.

Supply chain integration encompasses both internal integrations involving cross-functional coordination and external integration, facilitating collaboration with suppliers, customers, and logistics partners. Liu and Chiu (2021) found that supply chain digitalization directly improves internal integration ($\beta = 0.549$) and that integration partially mediates the digitalization-performance relationship. Liu et al. (2025) demonstrate that supply chain integration partially mediates digital transformation's effect on manufacturing resilience.

Supply chain capacity refers to operational resources, flexibility reserves, and scalability options available for executing resilience strategies. Elnadi (2025) demonstrates that supply chain capabilities mediate digital transformation's effect on sustainable performance outcomes. Iqbal et al. (2023) provide evidence that analytics adoption enhances both supply chain integration and flexibility, demonstrating interconnections among capability dimensions.

AIMS AND OBJECTIVES

The aim of this research is to investigate and quantify mechanisms through which logistics digital transformation influences supply chain resilience, with particular focus on identifying and comparing mediating roles of transparency, integration, and capacity as parallel transmission pathways.

Research objectives:

- examine the direct effect of digital transformation on supply chain resilience;
- assess the mediating role of supply chain transparency;
- evaluate the mediating role of supply chain integration;
- analyze the mediating role of supply chain capacity;
- compare the relative importance of different mediation pathways;
- develop a mathematical predictive model enabling quantitative estimation of resilience improvements.

Based on theoretical foundations and literature review, we hypothesize:

- **H1**: Digital transformation directly enhances supply chain resilience.
- **H2a**: Digital transformation enhances supply chain transparency.
- **H2b**: Transparency improves resilience.
- **H2c**: Transparency mediates the DT-resilience relationship.
- **H3a**: Digital transformation strengthens supply chain integration.
- **H3b**: Integration improves resilience.
- **H3c**: Integration mediates the relationship.
- **H4a**: Digital transformation enhances supply chain capacity.
- **H4b**: Capacity improves resilience.
- **H4c**: Capacity mediates the relationship.

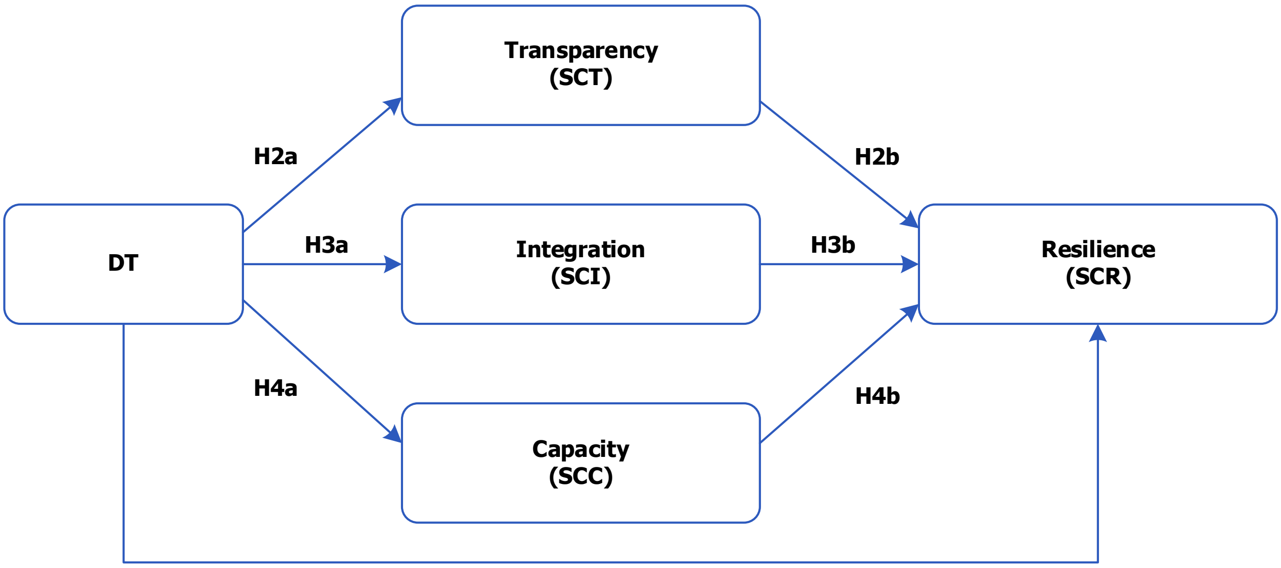

Figure 1. Conceptual research model (Primary Model). *Note: This is the primary model to be tested using a confirmatory approach.

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METHODS

Research Design and Participants

This study employed a cross-sectional survey design targeting supply chain and logistics professionals in the manufacturing and distribution sectors. Inclusion criteria:

- current employment in supply chain, logistics, or operations management role;
- minimum two years of organizational tenure;
- direct knowledge of organizational digital transformation initiatives. Exclusion criteria: incomplete responses failing attention checks, response times under 5 minutes suggesting careless responding, and straight-lining patterns.

Data collection occurred between January and April 2024 using an online questionnaire distributed through professional networks and industry associations. Settings included manufacturing facilities, distribution centers, and corporate logistics departments across Ukraine and European Union countries. Initial contact yielded 412 responses; after applying exclusion criteria, 287 valid responses remained (69.7% effective response rate).

Sample size was determined through a priori power analysis using G*Power 3.1 software. Parameters: $\alpha = 0.05$, statistical power = 0.80, medium effect size $f^2 = 0.15$, four predictors. Required minimum sample: $n = 138$. The obtained sample ($n = 287$) substantially exceeds this threshold, ensuring adequate statistical power for hypothesis testing and stable parameter estimation.

Participant characteristics: Industry distribution includes manufacturing (47.4%), logistics and transportation (28.2%), wholesale and distribution (15.3%), and retail (9.1%). Positions: supply chain managers (34.1%), operations directors (26.5%), logistics managers (21.6%), and senior executives (17.8%). Mean organizational tenure: 8.7 years ($SD = 4.2$). Mean industry experience: 12.3 years ($SD = 5.8$). Gender: male (61.3%), female (38.7%). Age range: 28-62 years ($M = 41.2$, $SD = 8.7$).

Ethical Considerations

This research was conducted in accordance with the Declaration of Helsinki ethical principles for research involving human subjects. The study protocol was reviewed and approved by the Ethics Committee of Kharkiv National Automobile and Highway University (Protocol No. 2024-01-15). All participants provided informed consent prior to questionnaire completion. Participation was voluntary with no incentives provided. Anonymity was ensured through the removal of identifying information. Data were stored securely with access restricted to research team members.

Measures

All constructs were measured using multi-item scales adapted from validated instruments. Items used a seven-point Likert format (1 = strongly disagree, 7 = strongly agree). Digital transformation was measured using 5 items adapted from Liu and Chiu (2021) and Zhao et al. (2023). Supply chain transparency used 4 items from Wang et al. (2024) and Tiwari et al. (2024). Supply chain integration used 5 items from Liu et al. (2025). Supply chain capacity used 4 items from Elnadi (2025). Supply chain resilience used 5 items from Zhao et al. (2023) and Dubey et al. (2021). Table 2 presents construct definitions and sample items.

Table 2. Construct definitions and measurement items. *(Source: compiled by authors. All items measured on 7-point Likert scale (1 = strongly disagree, 7 = strongly agree)*

Construct	Definition	Sample Items	Source
Digital Transformation (DT)	Strategic adoption of digital technologies to alter business processes and value creation	Core supply chain processes digitalized; Digital platforms for partner coordination; Data analytics guides decisions	Liu & Chiu (2021); Zhao et al. (2023)
Supply Chain Transparency (SCT)	Degree of shared access to accurate, timely information across the supply network	Real-time visibility into operations; Seamless information flows; Product traceability	Wang et al. (2024); Tiwari et al. (2024)
Supply Chain Integration (SCI)	Strategic collaboration through coordinated intra- and inter-organizational processes	Internal functions coordinated; Close collaboration with suppliers; Systems integrated	Liu et al. (2025); Liu & Chiu (2021)
Supply Chain Capacity (SCC)	Operational resources, flexibility reserves, and scalability options for resilience execution	Adequate capacity buffers; Operations scale rapidly; Alternative suppliers available	Elnadi (2025); Ning & Yao (2023)
Supply Chain Resilience (SCR)	Adaptive capability to prepare for, respond to, and recover from disruptions	Anticipate disruptions effectively; Respond quickly; Recover rapidly	Zhao et al. (2023); Dubey et al. (2021)

Analytical Approach

Data analysis employed partial least squares structural equation modeling (PLS-SEM) using SmartPLS 4.0 software. A strictly confirmatory approach was adopted: the primary model (Figure 1) was specified a priori based on theoretical foundations, and no post-hoc model modifications were performed. PLS-SEM was selected for prediction focus, ability to handle multiple mediating relationships, and robust performance with the obtained sample size (Hair et al., 2022). Bootstrap procedure specifications: 5,000 subsamples, bias-corrected confidence intervals, two-tailed testing, significance threshold $\alpha = 0.05$. Algorithm settings: path weighting scheme, maximum 300 iterations, stop criterion 10^{-7}. Missing data: listwise deletion (2.1% cases removed). Outliers: identified via Mahalanobis distance, no extreme outliers requiring removal. All constructs are specified as reflective. The analytical procedure followed Hair et al. (2022) two-stage protocol: (1) measurement model assessment through indicator reliability (loadings ≥ 0.708), internal consistency (composite reliability 0.70–0.95), convergent validity (AVE ≥ 0.50), and discriminant validity (HTMT < 0.85); (2) structural model assessment through path coefficients, R^2, f^2 effect sizes (small = 0.02, medium = 0.15, large = 0.35), and Q^2 predictive relevance. Mediation analysis used specific indirect effects with bias-corrected 95% confidence intervals.

RESULTS

Measurement Model Assessment

Table 3 presents measurement model results. All indicator loadings exceeded the 0.708 threshold (range: 0.724–0.891). Composite reliability values ranged from 0.867 to 0.921, exceeding the 0.70 criterion. Average variance extracted (AVE) values ranged from 0.621 to 0.744, surpassing the 0.50 threshold. Cronbach's alpha values ranged from 0.798 to 0.886. All variance inflation factor (VIF) values remained below 3.5, indicating the absence of multicollinearity.

Table 3. Measurement model results. Note: α = Cronbach's Alpha; ρc = composite reliability; AVE = average variance extracted; VIF = variance inflation factor.

Construct	Loadings	α	ρc	AVE	VIF
Digital Transformation (DT)	0.781–0.867	0.886	0.916	0.687	1.00
Supply Chain Transparency (SCT)	0.756–0.854	0.823	0.883	0.654	1.82
Supply Chain Integration (SCI)	0.789–0.891	0.874	0.921	0.744	2.14
Supply Chain Capacity (SCC)	0.724–0.832	0.798	0.867	0.621	1.67
Supply Chain Resilience (SCR)	0.768–0.879	0.856	0.897	0.636	—

Discriminant validity was assessed using the heterotrait-monotrait (HTMT) ratio. All HTMT values fell below the conservative 0.85 criterion (Table 4), confirming that constructs are empirically distinct.

Table 4. Discriminant validity: HTMT Matrix.

	DT	SCT	SCI	SCC	SCR
DT	—				
SCT	0.687	—			
SCI	0.723	0.793	—		
SCC	0.654	0.712	0.748	—	
SCR	0.698	0.756	0.812	0.689	—

Structural Model and Hypothesis Testing

The structural model explained substantial variance in all endogenous constructs: transparency ($R^2 = 0.312$), integration ($R^2 = 0.387$), capacity ($R^2 = 0.274$), and resilience ($R^2 = 0.583$). Stone-Geisser's Q^2 values confirmed predictive relevance: SCT ($Q^2 = 0.189$), SCI ($Q^2 = 0.267$), SCC ($Q^2 = 0.164$), SCR ($Q^2 = 0.402$). The interpreted model matches the originally specified primary model with no modifications. Table 5 presents complete hypothesis testing results.

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Table 5. Structural model results and hypothesis testing. Note: Bootstrap n = 5,000. SE = standard error. CI = bias-corrected confidence interval. f^2 interpretation: 0.02 = small, 0.15 = medium, 0.35 = large. VAF = Variance Accounted For.

Hypothesis / Path	β	SE	t-value	p	95% CI	f^2	Decision
H1: DT → SCR	0.190	0.056	3.412	<0.001	[0.081, 0.299]	0.08	Supported
H2a: DT → SCT	0.412	0.053	7.823	<0.001	[0.309, 0.515]	0.20	Supported
H2b: SCT → SCR	0.378	0.061	6.214	<0.001	[0.259, 0.497]	0.29	Supported
H3a: DT → SCI	0.523	0.054	9.647	<0.001	[0.417, 0.629]	0.38	Supported
H3b: SCI → SCR	0.379	0.064	5.891	<0.001	[0.253, 0.505]	0.35	Supported
H4a: DT → SCC	0.467	0.057	8.156	<0.001	[0.355, 0.579]	0.28	Supported
H4b: SCC → SCR	0.306	0.065	4.723	<0.001	[0.179, 0.433]	0.18	Supported
H2c: DT → SCT → SCR	0.156	0.035	4.512	<0.001	[0.088, 0.224]	—	Supported
H3c: DT → SCI → SCR	0.198	0.041	4.891	<0.001	[0.119, 0.277]	—	Supported
H4c: DT → SCC → SCR	0.143	0.037	3.845	<0.001	[0.070, 0.216]	—	Supported
Total: DT → SCR	**0.687**	**0.048**	**14.234**	**<0.001**	**[0.593, 0.781]**	**—**	**VAF=72.3%**

All three mediation hypotheses (H2c, H3c, H4c) were supported with significant indirect effects and confidence intervals excluding zero. The mediation type is complementary (partial) for all pathways: both direct and indirect effects are significant and operate in the same direction. Total indirect effect: 0.497 (sum of three pathways). VAF = 0.497/0.687 = 72.3%, indicating substantial mediation.

Mathematical Predictive Model

Based on empirical findings, we developed a mathematical predictive model for estimating supply chain resilience improvements. The general structural model is expressed in Equation (1):

$$SCR = \beta_0 + \beta_1(DT) + \beta_2(SCT) + \beta_3(SCI) + \beta_4(SCC) + \varepsilon \quad (1)$$

Mediator values as functions of digital transformation intensity:

$$SCT = 0.412 \times DT + \varepsilon_1 \quad (2)$$

$$SCI = 0.523 \times DT + \varepsilon_2 \quad (3)$$

$$SCC = 0.467 \times DT + \varepsilon_3 \quad (4)$$

Reduced-form total effect equation:

$$SCR = \beta_0 + 0.687 \times DT + \varepsilon \quad (5)$$

Table 6. Predictive model: pathway coefficients and percentage contributions. Note: Example: ΔDT = 2.0 → Expected ΔSCR = 0.687 × 2.0 = 1.374 units.

Pathway	Coefficient	Effect Type	% of Total	Interpretation
DT → SCR	0.190	Direct	27.7%	Technology-only effect
DT → SCT → SCR	0.156	Indirect	22.7%	Via transparency
DT → SCI → SCR	0.198	Indirect	28.8%	Via integration (strongest)
DT → SCC → SCR	0.143	Indirect	20.8%	Via capacity
Total Effect	0.687	Combined	100%	R^2 = 0.583

Prior to assessing indicator reliability, data screening procedures were conducted. Examination of missing values revealed 2.1% incomplete cases, which were removed through listwise deletion. Outlier analysis using Mahalanobis distance identified no extreme outliers requiring removal (all D^2 values below critical χ^2 at $p < 0.001$). Kolmogorov-Smirnov tests indicated minor deviations from normality for several indicators; however, PLS-SEM is robust to non-normal distributions, and bootstrapping procedures provide distribution-free significance testing.

Common method bias (CMB) was assessed using multiple procedures. Harman's single-factor test extracted five factors with eigenvalues exceeding 1.0, with the first factor accounting for 31.4% of variance—well below the 50% threshold indicating problematic CMB. Additionally, full collinearity assessment revealed all VIF values below 3.3 (range: 1.67–2.14), providing further evidence against substantial CMB influence on results.

Regarding indicator reliability, individual item loadings demonstrated strong relationships with their respective constructs. For Digital Transformation, loadings ranged from 0.781 to 0.867, with DT3 ("Our organization uses data analytics to guide strategic supply chain decisions") showing the highest loading (0.867) and DT1 ("Core supply chain processes have been digitalized") showing adequate but lower loading (0.781). Supply Chain Integration exhibited the strongest indicator reliability among constructs, with loadings ranging from 0.789 to 0.891. The highest loading item SCI4 ("Our information systems are seamlessly integrated with key partners") reflects the central role of technological integration in the construct. Supply Chain Capacity showed more variability in loadings (0.724–0.832), with SCC2 ("Our operations can scale rapidly when demand fluctuates") demonstrating the highest reliability.

Convergent validity was further supported by examining indicator cross-loadings. All items loaded more strongly on their intended constructs than on any other construct, with differences exceeding the recommended 0.10 threshold. The smallest difference observed was 0.127 (SCT2 loading on SCT versus SCI), confirming adequate discriminant validity at the indicator level. Model explanatory power was assessed through coefficient of determination (R^2) values for all endogenous constructs. The model explained 31.2% of the variance in Supply Chain Transparency ($R^2 = 0.312$), representing moderate explanatory power for this construct. This suggests that while digital transformation is a significant predictor, other factors not included in the model (such as organizational culture, leadership commitment, or industry regulations) also influence transparency levels. Supply Chain Integration showed a higher explained variance ($R^2 = 0.387$), indicating that digital transformation accounts for a substantial portion of integration capability development. Supply Chain Capacity exhibited lower explained variance ($R^2 = 0.274$), suggesting that capacity development depends more heavily on factors beyond digital transformation, such as financial resources, supplier relationships, and infrastructure investments. For the primary endogenous construct, Supply Chain Resilience, the model achieved substantial explanatory power with $R^2 = 0.583$, indicating that digital transformation, together with the three mediators, explains 58.3% of variance in resilience outcomes. This compares favorably with prior research: Zhao et al. (2023) reported $R^2 = 0.47$ for resilience, and Liu et al. (2025) achieved $R^2 = 0.52$. The adjusted R^2 value of 0.577 confirms that explanatory power is not artificially inflated by the number of predictors. Effect sizes (f^2) provide insight into the practical significance of each relationship beyond statistical significance. Following Cohen's guidelines as applied by Hair et al. (2022), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. The direct effect of digital transformation on resilience ($f^2 = 0.08$) represents a small-to-medium effect, indicating a modest unique contribution when mediators are controlled. In contrast, Supply Chain Integration's effect on resilience ($f^2 = 0.35$) represents a large effect, demonstrating that integration is the most influential predictor of resilience among the mediators. Transparency ($f^2 = 0.29$) and Capacity ($f^2 = 0.18$) show medium-to-large and medium effects, respectively.

Predictive relevance was assessed through Stone-Geisser's Q^2 values obtained via a blindfolding procedure with omission distance $d = 7$. All Q^2 values substantially exceeded zero: SCT ($Q^2 = 0.189$), SCI ($Q^2 = 0.267$), SCC ($Q^2 = 0.164$), and SCR ($Q^2 = 0.402$). These values confirm that the model provides predictions exceeding simple mean prediction, with resilience showing particularly strong predictive relevance. The q^2 effect sizes for predictive relevance ranged from 0.04 to 0.18, indicating small to medium predictive contributions from individual predictors.

DISCUSSION

Summary of Hypothesis Testing

All ten hypotheses were supported by empirical evidence. H1 (direct effect) was supported: digital transformation directly enhances resilience ($\beta = 0.190$, $p < 0.001$), though with a small-to-medium effect size ($f^2 = 0.08$). H2a-c (transparency pathway) was supported: DT enhances transparency ($\beta = 0.412$), transparency improves resilience ($\beta = 0.378$), and the indirect effect is significant (0.156). H3a-c (integration pathway) were supported with the strongest effects: DT enhances integration ($\beta = 0.523$), integration improves resilience ($\beta = 0.379$, $f^2 = 0.35$, large effect), and the indirect effect is largest among mediators (0.198). H4a-c (capacity pathway) were supported: DT enhances capacity ($\beta = 0.467$), capacity improves resilience ($\beta = 0.306$), and the indirect effect is significant (0.143).

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Theoretical Implications

This study advances supply chain management theory by revealing that approximately 72% of the digital transformation's effect on resilience operates through mediated pathways. This finding challenges simplified conceptualizations treating digitalization as directly producing resilience outcomes. Integration emerges as the strongest mediator (28.8% of total effect), consistent with Liu and Chiu (2021) and Liu et al. (2025). However, our multi-mediator model reveals complementary rather than redundant pathways.

We contribute to theoretical integration by demonstrating how Dynamic Capabilities Theory, Resource-Based View, and Information Processing Theory provide complementary explanations. DCT's sensing-seizing-reconfiguring framework maps onto transparency-integration-capacity mechanisms. RBV explains the digital transformation's creation of inimitable capabilities. IPT explains transparency's role in managing uncertainty through enhanced information processing.

Practical Implications

Findings offer actionable guidance for practitioners. Organizations achieving high digitalization but neglecting mediator development capture only 27.7% of potential resilience benefits. Investment in integration platforms offers the highest returns (28.8% contribution), consistent with Mukha and Popova's (2025) recommendations regarding SaaS adoption. The predictive model enables quantitative business case development: a 2.0-unit DT increase yields an expected 1.374-unit resilience improvement.

Limitations and Threats to Validity

Several limitations warrant acknowledgment. Internal validity threats: cross-sectional design precludes causal inference despite theoretical grounding; self-reported measures may introduce common method variance despite procedural controls (temporal separation, anonymity, reverse-coded items). Statistical conclusion validity: while sample size exceeds power requirements, Type I error rates may be inflated across multiple hypothesis tests. External validity threats: samples from manufacturing and logistics sectors in Ukraine and the EU may limit generalizability to other contexts. Construct validity: adapted scales performed well (all AVE > 0.50) but may not fully capture constructs in different cultural settings. Unmeasured confounders (organizational size, industry sub-sector, digital maturity baseline) may influence observed relationships.

CONCLUSIONS

This study investigated mechanisms through which logistics digital transformation influences supply chain resilience using PLS-SEM with data from 287 supply chain professionals. The primary model was tested using a confirmatory approach with no post-hoc modifications. All ten hypotheses were supported. Digital transformation's total effect ($\beta = 0.687$) substantially exceeds the direct effect ($\beta = 0.190$), with 72.3% operating through mediated pathways. Integration demonstrates the strongest mediation (0.198), followed by transparency (0.156) and capacity (0.143). The model explains 58.3% of resilience variance with confirmed predictive relevance ($Q^2 = 0.402$). Theoretical contributions include an integrated multi-mediator framework revealing differentiated roles: transparency as information enabler, integration as coordination mechanism, capacity as execution amplifier. Practical contributions include a quantitative predictive model and evidence that technology adoption alone captures less than one-third of potential benefits.

Future research should employ longitudinal designs, extend to other sectors and regions, incorporate objective performance measures, and examine boundary conditions affecting mediator importance.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

Conceptualization: *Taras Mukha*
Data curation: *Taras Mukha*
Formal Analysis: *Nadiia Popova*
Methodology: *Taras Mukha*
Software: *Taras Mukha*
Resources: *Taras Mukha*
Supervision: *Nadiia Popova*

Validation: *Nadiia Popova*
Investigation: *Taras Mukha*
Visualization: *Taras Mukha*
Project administration: *Nadiia Popova*
Writing – review & editing: *Nadiia Popova*
Writing – original draft: *Taras Mukha*

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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Муха Т., Попова Н.

ВПЛИВ ЦИФРОВОЇ ТРАНСФОРМАЦІЇ НА СТІЙКІСТЬ ЛАНЦЮГІВ ПОСТАЧАННЯ

Мета дослідження полягає у виявленні та кількісній оцінці механізмів, через які цифрова трансформація логістики впливає на стійкість ланцюгів постачання. Актуальність зумовлена зростанням волатильності глобального середовища та потребою в науково обґрунтованих підходах до підвищення резильєнтності ланцюгів постачання в умовах цифровізації.

Методологія дослідження базується на моделюванні структурними рівняннями методом часткових найменших квадратів (PLS-SEM) із використанням програмного забезпечення SmartPLS 4.0. Теоретичний фундамент інтегрує сучасні концепції динамічних спроможностей, ресурсного підходу та теорії обробки інформації. Емпіричний аналіз ґрунтується на даних анкетування 287 фахівців з управління ланцюгами постачання. Розмір вибірки обґрунтовано за допомогою аналізу статистичної потужності (G*Power: $\alpha = 0{,}05$, power = 0,80, $f^2 = 0{,}15$). Застосовано бутстреп-процедуру з 5000 підвибірок для розрахунку довірчих інтервалів.

Результати демонструють, що модель пояснює 58,3% дисперсії стійкості ланцюга постачання ($R^2 = 0{,}583$) з підтвердженою прогностичною релевантністю ($Q^2 = 0{,}402$). Цифрова трансформація чинить значущий позитивний вплив на всі три медіатори: прозорість ($\beta = 0{,}412$, $p <0{,}001$), інтеграцію ($\beta = 0{,}523$, $p <0{,}001$) та потужність ($\beta = 0{,}467$, $p <0{,}001$). Загальний ефект на стійкість ($\beta = 0{,}687$, 95% ДІ [0,593; 0,781]) суттєво перевищує прямий вплив ($\beta = 0{,}190$). Інтеграція демонструє найсильніший медіаційний ефект ($f^2 = 0{,}35$), за нею прозорість ($f^2 = 0{,}29$) і потужність ($f^2 = 0{,}18$). Приблизно 72% загального ефекту реалізується через опосередковані механізми (VAF = 72,3%).

Наукова новизна полягає в розробці інтегрованої багатомедіаторної моделі з математичним апаратом прогнозування покращень стійкості від інвестицій у цифрову трансформацію. Практичне значення: організації, що досягають високого рівня цифровізації без розвитку медіаторних спроможностей, реалізують лише 27,7% потенційних переваг стійкості. Пріоритетними є інвестиції в інтеграційні платформи (28,8% загального ефекту).

Ключові слова: цифрова трансформація; стійкість ланцюга постачання; PLS-SEM; прозорість ланцюга постачання; інтеграція ланцюга постачання; потужність ланцюга постачання; медіаційний аналіз; логістика

JEL Класифікація: L81, L91, M11, O33, Q55