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The Impact of Digital Transformation on Supply Chain Resilience to Environmental Shocks: The Mediating Role of Supply Chain Integration

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ABSTRACT

Severe climate events and abrupt environmental compliance rules frequently stall multi-tier manufacturing operations. Firms often respond by pouring capital into digital upgrades predictive software, sensor tracking, and enterprise software suites. Yet plants still sit idle during acute ecological disruptions. This paper examines this disconnect, known as the digital paradox, by assessing how supply chain integration mediates between digital tools and operational resilience. We surveyed 284 operations and logistics directors across manufacturing plants that recently endured climate-related disruptions. Modeling the data via Partial Least Squares Structural Equation Modeling (PLS-SEM), we found that digital capability does support resilience on its own ($\beta = 0.218, p < 0.001$), but most of the operational benefit flows indirectly through supply chain integration ($\beta = 0.358, p < 0.001$), accounting for 52.8% of resilience variance overall. Supplier integration carries the heaviest burden ($\beta = 0.160$), followed by cross-functional internal integration ($\beta = 0.111$) and customer integration ($\beta = 0.087$). Tracking tools and predictive algorithms provide early signals, but they remain passive monitors without aligned supplier contracts, shared safety buffers, and unified operational routines. Building resilient networks require firms to treat digital software as an enabler for joint coordination rather than a replacement for collaborative relationships.

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I. INTRODUCTION

Industrial supply lines are breaking more often under ecological pressures (Craighead et al., 2007; Wagner & Neshat, 2013). Extreme storms, long dry spells that drain commercial river channels, and sudden heat waves that shut down power grids are no longer isolated incidents; they have turned into routine hazards for plant managers (Sarkis, 2021; Sheffi, 2005). At the same time, regional carbon adjustments, sudden emissions limits, and strict ecological bans force procurement teams to rethink materials on tight deadlines (Zhu et al., 2007). These events behave differently from normal market shifts or local equipment downtime. A flash flood in an industrial corridor does not simply delay one shipment; it cuts off secondary component suppliers, jams rail depots, and quickly creates shortages across an entire multi-tier network (Ivanov, 2020). For plant managers and logistics directors, building supply chain resilience (SCRes) the ability to spot disruptions early, absorb initial damage, and resume production quickly has become a condition for survival (Tse et al., 2011).

To protect themselves, manufacturers continue to spend heavily on digital upgrades (Hofmann & Rüsch, 2017; Fosso Wamba et al., 2017). Facilities install Internet of Things (IoT) sensors along transport corridors, build predictive models using machine learning,

and set up cloud-based Enterprise Resource Planning (ERP) platforms (Hofmann & Rüsch, 2017). The core idea seems clear: real-time feeds and predictive algorithms should identify weather threats earlier, helping operations teams reroute cargo, shift run times, and secure backup stock before warehouses grind to a halt (Teece et al., 1997).

In practice, this promise often falls flat. Industry reports and operations management studies document a stubborn "digital paradox" (Gebauer et al., 2005; Mario et al., 2023). Despite sizable IT budgets, firms frequently see negligible improvements in how fast they bounce back from environmental crises (Min et al., 2001). The problem is that technology gets trapped in departmental silos (Rai et al., 2006). A focal manufacturer might maintain an advanced dashboard showing weather impacts across transit corridors, but if tier-1 and tier-2 suppliers use incompatible legacy software or guard operational numbers behind firewalls, that visibility remains useless (Autry et al., 2010). When a storm knocks out a key raw materials plant, knowing it two hours earlier makes little difference if the buyer has no established protocol to reallocate orders to an alternative vendor (Autry et al., 2010). Software can flag bottlenecks, but it cannot fix them without inter-firm cooperation on the ground (Lee, 2004).

Resolving this tension requires looking closely at how information turns into physical action across organizational boundaries (Cao & Zhang, 2011). Drawing on Information Processing Theory (IPT; Galbraith, 1973) and the Dynamic Capabilities View (DCV; Teece et al., 1997), we argue that supply chain integration (SCI) serves as the necessary bridge between digital tools and genuine physical recovery. Digital investments provide raw processing speed and data visibility, but supply chain integration uniting internal functions, upstream suppliers, and downstream buyers provides the working relationships, shared platforms, and contingency plans needed to act on those alerts (Dyer & Singh, 1998; Flynn et al., 2010).

II. THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

Theoretical Integration: Information Processing Theory and Dynamic Capabilities

Understanding how IT investments protect manufacturing operations during severe weather events requires bridging Information Processing Theory (IPT; Galbraith, 1973) with the Dynamic Capabilities View (DCV; Teece et al., 1997). Galbraith's (1973) core premise remains straightforward: when an organization faces abrupt environmental shocks, the information it needs to run daily operations quickly outstrips what its existing reporting channels can handle. Extreme climate events, whether sudden floods halting rail spurs or prolonged droughts shutting down barge traffic create massive operational blind spots (Craighead et al., 2007; Ivanov, 2020).

Digital tools directly expand that processing bandwidth (Fosso Wamba et al., 2017; Hofmann & Rüsch, 2017). Telemetry sensors, automated logistics trackers, and cloud analytics ingest field conditions in seconds, reducing uncertainty (Hofmann & Rüsch, 2017). Yet raw data volume alone cannot solve an operational breakdown (Galbraith, 1973). Without pre-established organizational pipes, digital alerts simply pool inside internal servers (Rai et al., 2006). Supply chain integration acts as those conduits, routing operational intelligence across corporate firewalls so managers and external partners can react before assembly lines stall (Flynn et al., 2010).

Dynamic capabilities explain how firms turn that information into physical survival (Teece et al., 1997). Rather than viewing dynamic capabilities as abstract corporate virtues, we follow Teece et al.'s (1997) behavioral perspective: organizations survive turbulence by continuously sensing shifts, seizing fleeting opportunities, and reallocating core operational assets. In our context, digital transformation provides the technological infrastructure to sense external disruption (Fosso Wamba et al., 2017). Supply chain integration creates the governance mechanisms to seize collaborative fixes such as reassigning purchase volumes or sharing buffer inventory (Cao & Zhang, 2011; Flynn et al., 2010). Finally, supply chain resilience represents the tangible outcome: plants absorb component shocks, activate backup freight lanes, and return to standard operating cadence (Sheffi, 2005; Tse et al., 2011).

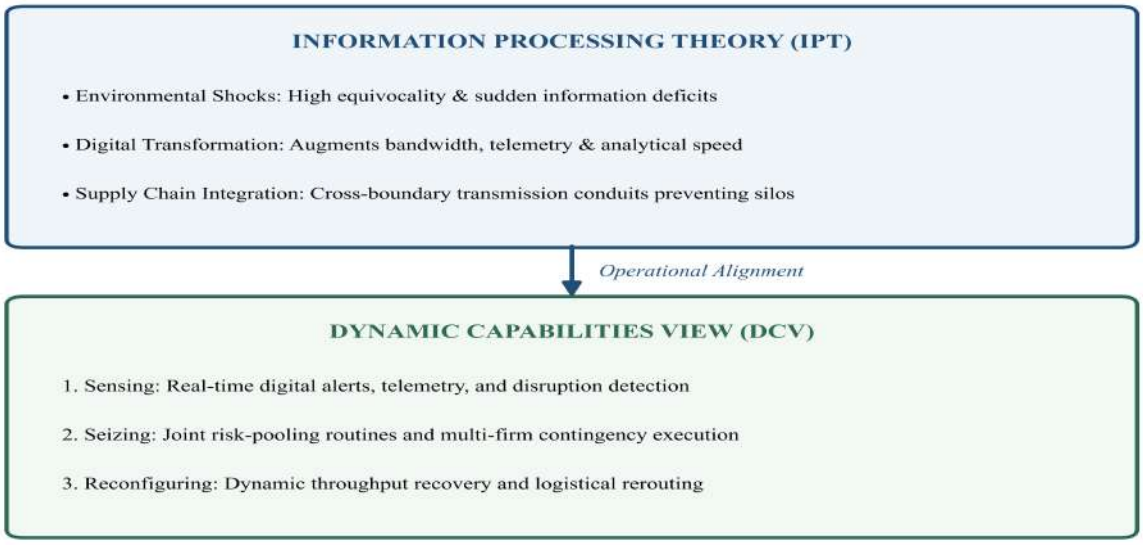

Fig. 1. Theoretical integration architecture synthesizing IPT and DCV.

Conceptual Framework and Construct Delineation

Our research framework models digital transformation as a second-order antecedent driving three distinct operational integration conduits (internal, supplier, and customer integration), which in turn support multi-dimensional supply chain resilience. We define the operational boundaries of each construct in Table I.

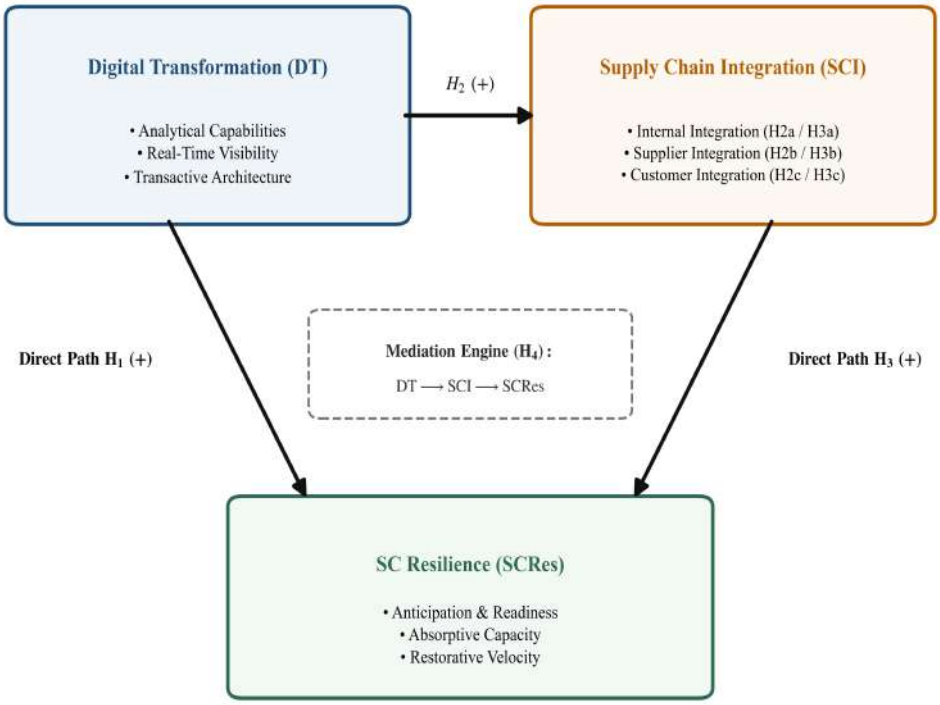

Fig. 2. Structural conceptual framework showing direct and mediated paths.

Table I: Operationalized Theoretical Constructs and Multi-Dimensional Sub-Domains

Construct	Structural Dimension	Operational Scope & Indicator Focus	Theoretical Anchor
Digital Transformation (DT)	Analytical Capabilities (DT-AC)	Predictive ML, digital twins, disruption simulation algorithms.	Fosso Wamba et al. (2017)
	Real-Time Visibility (DT-VI)	IoT sensors, RFID asset tagging, satellite tracking, telemetry.	Hofmann & Rüsch (2017)
	Transactive Infrastructure (DT-TI)	Unified cloud ERP, standardized API gateways, distributed ledgers.	Rai et al. (2006)
Supply Chain Integration (SCI)	Internal Integration (SCI-II)	Cross-functional ERP synchronicity across procurement and logistics.	Flynn et al. (2010)
	Supplier Integration (SCI-SI)	Upstream shared risk mitigation, collaborative capacity allocation.	Prajogo & Olhager (2012)
	Customer Integration (SCI-CI)	Downstream demand signal visibility, dynamic service renegotiation.	Cao & Zhang (2011)
Supply Chain Resilience (SCRes)	Anticipation & Readiness (SCR-AR)	Disruption lead-time detection, advance warning horizon.	Craighead et al. (2007)
	Absorptive Capacity (SCR-AB)	Structural network robustness, maintenance of core throughput.	Sheffi (2005)
	Restorative Velocity (SCR-RV)	Time-to-recover (TTR), alternative routing agility, post-shock recovery.	Tse et al. (2011)

Hypotheses Development

Digital Transformation and Supply Chain Resilience (H1)

Digital transformation provides the foundational analytical architecture and field visibility necessary to mitigate severe operational shocks (Fosso Wamba et al., 2017). Through predictive machine learning models, telemetry-based asset tracking, and standardized

transactive platforms, manufacturers can detect climate and environmental anomalies before they cascade through the supply network (Hofmann & Rüsch, 2017). From a dynamic capability's perspective, digital sensing tools significantly compress the time window required to recognize vulnerabilities, evaluate alternative sourcing options, and execute emergency rerouting protocols (Teece et al., 1997). Consequently, standalone investments in digital infrastructure provide direct capabilities that reduce recovery lead times and sustain core plant operations during environmental crises.

$\boldsymbol{H_1}$**:** Digital transformation positively influences supply chain resilience.

Digital Transformation and Supply Chain Integration (H2a–H2c)

Departmental friction often boils down to fragmented data systems and administrative delays (Galbraith, 1973; Rai et al., 2006). Digital platforms eliminate manual handoffs by establishing a shared data layer (Prajogo & Olhager, 2012). Internally, enterprise cloud platforms let procurement, warehousing, and production planners track the exact same production figures simultaneously (Flynn et al., 2010). Externally, secure APIs and EDI feeds pull strategic suppliers and key distributors into that visibility loop (Rai et al., 2006). Sharing production schedules and container milestones automatically lowers coordination costs and builds inter-firm trust (Cao & Zhang, 2011; Prajogo & Olhager, 2012). When partners see the same numbers in real time, coordinating joint responses becomes second nature (Hofmann & Rüsch, 2017).

$\boldsymbol{H_{2a}}$**:** Digital transformation positively influences internal integration.

$\boldsymbol{H_{2b}}$: Digital transformation positively influences supplier integration.

$\boldsymbol{H_{2c}}$: Digital transformation positively influences customer integration.

Supply Chain Integration and Supply Chain Resilience (H3a–H3c)

Algorithms can highlight risk, but they cannot move freight or authorize overtime (Autry et al., 2010; Lee, 2004). That execution depends on collaborative relationships and shared routines (Dyer & Singh, 1998). When extreme weather takes out a primary manufacturing hub, tight internal integration keeps sales, procurement, and production aligned, preventing departments from hoarding local stock or making conflicting promises to clients (Flynn et al., 2010).

Upstream, integrated relationships with suppliers prove decisive (Prajogo & Olhager, 2012). Suppliers who share visibility and joint contingency plans can quickly pivot tooling or release reserved capacity without lengthy contract disputes (Lee, 2004; Scholten & Schilder, 2015). Downstream, integrated communication with customers prevents panicked over-ordering, allowing focal firms to allocate scarce inventory rationally while keeping major accounts informed (Cao & Zhang, 2011).

H3a: Internal integration positively influences supply chain resilience.

H3b: Supplier integration positively influences supply chain resilience.

H3c: Customer integration positively influences supply chain resilience.

The Mediating Role of Supply Chain Integration (H4a–H4c)

The digital paradox arises when firms mistake software adoption for operational preparedness (Gebauer et al., 2005; Mario et al., 2023). Information Processing Theory makes the underlying breakdown clear: collecting millions of data points does no good if organizational barriers prevent that insight from turning into joint physical action (Galbraith, 1973). An automated alert warning of a factory shutdown upstream cannot protect a manufacturer if the firm lacks relational routines with alternative suppliers to absorb the shortfall (Autry et al., 2010; Scholten & Schilder, 2015).

Supply chain integration bridges this gap (Cao & Zhang, 2011). Internal integration aligns cross-functional priorities, supplier integration activates physical component workarounds, and customer integration stabilizes the order book (Flynn et al., 2010; Prajogo & Olhager, 2012). Without these collaborative conduits, digital infrastructure functions merely as a high-priced monitoring system that records disruptions without resolving them (Lee, 2004).

$\boldsymbol{H_{4a}}$**:** Internal integration mediates the relationship between digital transformation and supply chain resilience.

$\boldsymbol{H_{4b}}$**:** Supplier integration mediates the relationship between digital transformation and supply chain resilience.

$\boldsymbol{H_{4c}}$**:** Customer integration mediates the relationship between digital transformation and supply chain resilience.

Table II: Structural Model Hypothesis Paths and Theoretical Rationales

Hypothesis	Path Trajectory	Theoretical Justification	Expected Direction
H1	DT -> SCRes	DCV: Advanced sensing and predictive modeling reduce response time.	Positive (+)
H2a	DT -> SCI-II	IPT: Cross-functional cloud platforms resolve departmental silos.	Positive (+)
H2b	DT -> SCI-SI	IPT: Shared APIs lower upstream coordination transaction costs.	Positive (+)
H2c	DT -> SCI-CI	IPT: Real-time telemetry enhances downstream demand transparency.	Positive (+)

H3a	SCI-II -> SCRes	DCV: Internal alignment accelerates structural resource reallocation.	Positive (+)
H3b	SCI-SI -> SCRes	DCV: Joint supplier routines enable rapid component substitution.	Positive (+)
H3c	SCI-CI -> SCRes	DCV: Demand-side integration mitigates post-shock bullwhip distortions.	Positive (+)
H4a	DT -> SCI-II -> SCRes	IPT/DCV: Internal data routing channels digital alerts into response.	Positive (+)
H4b	DT -> SCI-SI -> SCRes	IPT/DCV: Upstream relational mechanisms execute digital plans.	Positive (+)
H4c	DT -> SCI-CI -> SCRes	IPT/DCV: Customer integration stabilizes distribution based on alerts.	Positive (+)

III. RESEARCH METHODOLOGY

Sampling Strategy and Data Collection

We tested our hypotheses using cross-sectional survey data collected from mid-to-large manufacturing plants operating in sectors heavily exposed to environmental hazards: automotive manufacturing, chemicals and processing, industrial machinery, electronics, and food and agribusiness (Craighead et al., 2007; Zhu et al., 2007). We pulled our sample frame from commercial business registries (Dun & Bradstreet and Bureau van Dijk ORBIS).

To qualify, facilities had to meet three operational criteria:employ at least 100 full-time staff, have actively deployed digital supply chain initiatives over the prior two years, and operate in geographic zones that experienced documented climate disruptions within the previous 36 months. We specifically targeted key informants holding senior operational oversight Vice Presidents of Supply Chain, Operations Directors, and Chief Procurement Officers because their roles span organizational boundaries.

We distributed the questionnaire online following the tailored design principles outlined by Dillman et al. (2014), sending personalized reminders across three successive contact waves. From an initial pool of 1,200 eligible facilities, we retrieved 312 complete questionnaires. After removing 28 submissions due to straight-lining or incomplete sections, we retained 284 usable responses, yielding an effective response rate of 23.67%. Table 3 breaks down our respondent profile.

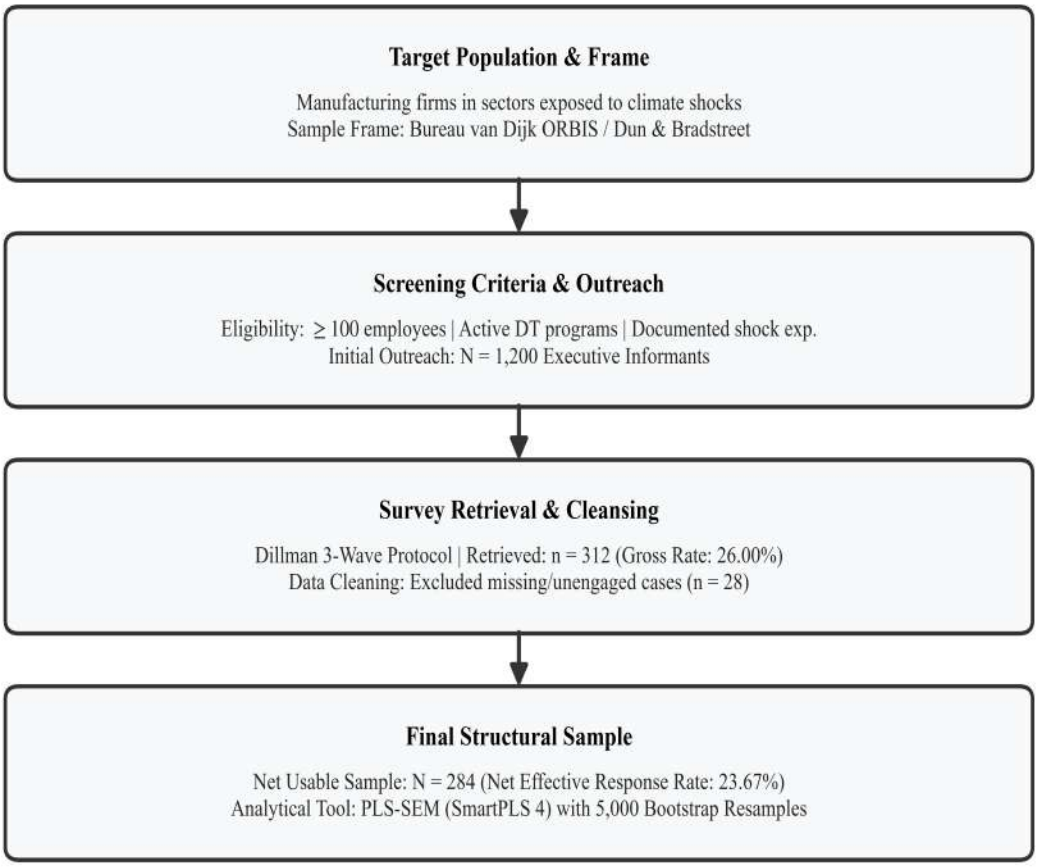

Fig. 3. Sampling workflow and empirical filtering pipeline.

Table III: Demographic Profile of Responding Firms and Key Informants (N = 284)

Attribute	Classification / Interval	Frequency (n)	Percentage (%)
Industry Sector	Automotive & Industrial Machinery	82	28.87%
	Chemicals & Process Manufacturing	64	22.54%
	Electronics & Electrical Equipment	78	27.46%
	Food, Beverage & Agribusiness	60	21.13%
Firm Size (Employees)	100-249 (Medium enterprise)	88	30.99%
	250-999 (Mid-to-large enterprise)	124	43.66%
	>= 1,000 (Large multinational)	72	25.35%
Annual Revenue (USD)	Less than $50M	54	19.01%
	$50M-$250M	136	47.89%
	Greater than $250M	94	33.10%
Respondent Position	VP / Director of Supply Chain / Logistics	108	38.03%
	Chief Operating Officer / Operations Director	86	30.28%
	Procurement / Sourcing Director	52	18.31%
	Head of Digital Transformation / SC Systems	38	13.38%
Organizational Tenure	Less than 5 years	36	12.68%
	5-10 years	142	50.00%
	Greater than 10 years	106	37.32%

Non-Response Bias Testing

Because survey timing can introduce systematic participation bias, we compared early responses ($n = 210$) against those received after the final reminder wave ($n = 74$) following the extrapolation procedure recommended by Armstrong and Overton (1977). Independent-sample t-tests across continuous demographic metrics (firm size and firm age) as well as the main construct scores revealed no statistically meaningful differences between early and late cohorts ($p > 0.45$). Similarly, a contingency chi-square test across industry distributions showed no divergence ($\chi^2 = 2.418, p = 0.490$). Non-response bias does not appear to distort our sample (Armstrong & Overton, 1977).

Table IV: Assessment of Non-Response Bias: Independent Samples t-Tests

Assessment Variable	Early Mean (n = 210)	Late Mean (n = 74)	Mean Diff	t-statistic	p-value (2-tailed)
Firm Size (ln Employees)	5.84	5.79	0.05	0.542	0.588
Firm Age (Years)	24.16	23.38	0.78	0.496	0.620
Digital Transformation (DT)	3.76	3.71	0.05	0.638	0.524
Supply Chain Integration (SCI)	3.68	3.62	0.06	0.712	0.477
SC Resilience (SCRes)	3.54	3.59	-0.05	-0.601	0.548

Common Method Bias (CMB) Mitigation and Diagnostic Checks

Because our data relies on single informants completing self-reported surveys, we applied both preventative questionnaire design choices and post-hoc statistical checks to guard against common method bias (Podsakoff et al., 2003). During survey administration, we guaranteed informant anonymity, separated the dependent resilience indicators from independent digital transformation questions, and varied scale anchors across sections (Podsakoff et al., 2003).

Statistically, Harman's single-factor test showed that the first unrotated principal component explained only 26.42% of total variance, well below the traditional 50% ceiling (Podsakoff et al., 2003). Second, we introduced an unrelated three-item marker variable into the structural model; its average correlation with target variables was negligible ($r_m = 0.038$) and left all structural path coefficients significant (Lindell & Whitney, 2001). Finally, full collinearity tests yielded variance inflation factors between 1.42 and 2.18 across all latent dimensions, safely below the conservative 3.3 threshold (Kock, 2015). Common method bias is not a confounding factor in this dataset.

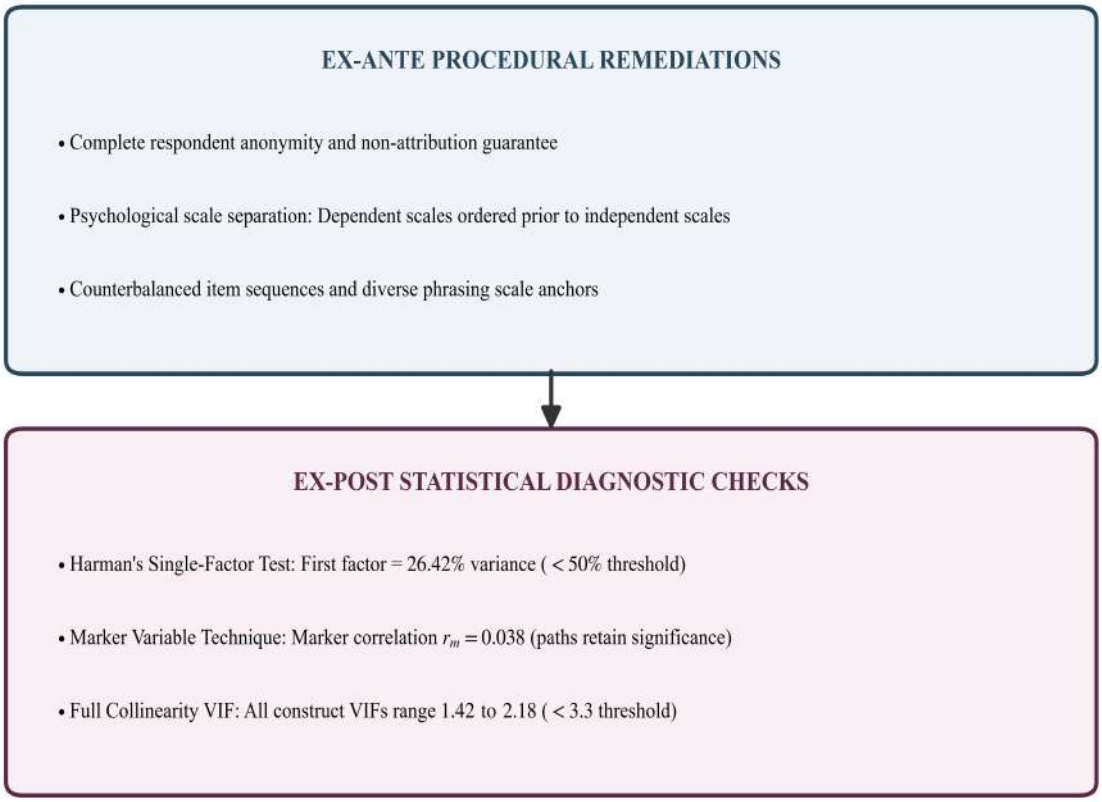

Fig. 4. Dual-stage common method bias governance protocol.

Construct Operationalization and Measurement Scales

We adapted our survey items from peer-reviewed scales in supply chain and operations management, tailoring the wording specifically to disruption contexts. Every indicator used a 5-point Likert scale (1 = "Strongly Disagree" to 5 = "Strongly Agree"). Control variables were captured as follows: *Firm Size* was operationalized as the natural logarithm of full-time employees (ln Employees); *Firm Age* was measured as the total years since incorporation; *Supply Chain Geographic Dispersion (SC Geo. Disp.)* was measured using a categorical index tracking the geographic spread of Tier-1 and Tier-2 suppliers (local, regional, national, global); and *Environmental Dynamism* was operationalized via a validated three-item Likert scale. Table 5 lists all survey items.

Table V: Complete Measurement Scales and Survey Indicators

Latent Construct / Dimension	Code	Measurement Scale Item Content
DT: Analytical Capabilities	DT-AC1	Our firm utilizes predictive algorithms to identify supply chain failure vulnerabilities.
	DT-AC2	We run digital simulation models (digital twins) to assess disruptions under extreme environmental conditions.
	DT-AC3	Our analytical platforms dynamically suggest optimal mitigation routes during supply anomalies.
	DT-AC4	Machine learning tools forecast raw material yield disruptions driven by weather events.
DT: Real-Time Visibility	DT-VI1	IoT sensors and telemetry track cargo conditions and transit milestones in real time.
	DT-VI2	Critical supplier inventory levels are monitored continuously through shared digital dashboards.
	DT-VI3	Automated alerts are triggered across our network when environmental events threaten transit routes.
	DT-VI4	We maintain end-to-end digital traceability down to Tier-2 suppliers for key components.
DT: Transactive Architecture	DT-TI1	Standardized API middleware facilitates seamless data interchange across partner systems.

	DT-TI2	Cloud platforms provide a single, unified source of operational truth across all business units.
	DT-TI3	Digital interfaces automate data interchange between our ERP and core supply chain nodes.
SCI: Internal Integration	SCI-II1	Procurement, production, and logistics teams maintain unified operational planning data.
	SCI-II2	Cross-functional teams resolve operational bottlenecks collaboratively.
	SCI-II3	Critical shock-response plans are developed jointly across internal departments rather than within silos.
	SCI-II4	Information flows freely and without organizational friction across all operational units.
SCI: Supplier Integration	SCI-SI1	We share rolling forecasts and real-time production schedules with strategic tier-1 suppliers.
	SCI-SI2	We collaborate closely with primary suppliers to establish joint environmental risk contingency protocols.
	SCI-SI3	Strategic suppliers are directly involved in our operational planning and safety stock configurations.
	SCI-SI4	We maintain joint problem-solving routines with suppliers when supply disruptions manifest.
SCI: Customer Integration	SCI-CI1	We share operational inventory and production availability data with key customers.
	SCI-CI2	Joint replenishment planning is conducted collaboratively with our major distributors and clients.
	SCI-CI3	We work closely with key customers to dynamically reprioritize orders during supply emergencies.
	SCI-CI4	Customer demand adjustments are integrated directly into our scheduling systems without transmission delays.
SCRes: Anticipation & Readiness	SCR-AR1	Our supply chain detects early warning signals of environmental hazards well before operations are affected.
	SCR-AR2	We maintain proactive contingency reserves and alternative routing protocols for high-risk climate zones.
	SCR-AR3	Our organization regularly stresses emergency readiness against extreme environmental shock scenarios.
SCRes: Absorptive Capacity	SCR-AB1	Our supply chain absorbs acute weather and environmental shocks without significant downtime.
	SCR-AB2	During climate disruptions, our core production rates remain stable through localized mitigation measures.
	SCR-AB3	Buffer inventories and pre-allocated capacity absorb critical input shortfalls during ecological disruptions.
SCRes: Restorative Velocity	SCR-RV1	When an environmental shock hits, our network returns to normal operational throughput rapidly.
	SCR-RV2	We rapidly activate secondary sourcing agreements and freight rerouting if primary corridors fail.
	SCR-RV3	Time-to-recover (TTR) from acute ecological disruptions is minimized across our multi-tier operations.
Control: Environmental Dynamism	ED-1	The frequency of climate-driven operational disruptions has increased noticeably over the last 36 months.
	ED-2	Environmental and ecological regulations governing our sector shift rapidly and unpredictably.
	ED-3	Weather anomalies and environmental shocks create high baseline volatility in raw material access.

IV. DATA ANALYSIS AND EMPIRICAL RESULTS

We estimated our structural model using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4 (Hair et al., 2022). PLS-SEM fits our analytical goals because our framework combines a higher-order construct (digital transformation), models complex mediation pathways, and focuses on maximizing explained variance in an operational outcome under real-world distributional conditions. Digital transformation was operationalized as a reflective-reflective second-order construct using the standard two-stage embedded approach. We evaluated the results across two sequential stages: the measurement model and the structural model.

A. Measurement Model Assessment

We checked indicator reliability, internal consistency, and convergent validity across all first-order scales. As Table 6 shows, every outer loading exceeded 0.74 (well above the 0.708 cutoff) with high statistical significance ($p < 0.001$). Composite reliability (ρ_c) and Cronbach's alpha values ranged from 0.812 to 0.922, confirming strong scale reliability. Convergent validity was equally sound: Average Variance Extracted (AVE) values ranged from 0.612 to 0.759, surpassing the 0.50 threshold across all dimensions (Hair et al., 2022).

Table VI: Measurement Model Assessment: Standardized Factor Loadings, Reliability, and Convergent Validity (N = 284)

Construct / Dimension	Code	Loading (lambda)	SE	t-stat	alpha	CR (rho_c)	AVE
Analytical Capabilities (DT-AC)	DT-AC1	0.824	0.024	34.333	0.865	0.908	0.712
	DT-AC2	0.856	0.021	40.762			
	DT-AC3	0.861	0.020	43.050			
	DT-AC4	0.834	0.023	36.261			
Real-Time Visibility (DT-VI)	DT-VI1	0.804	0.026	30.923	0.871	0.912	0.722
	DT-VI2	0.849	0.022	38.591			
	DT-VI3	0.872	0.019	45.895			
	DT-VI4	0.873	0.019	45.947			
Transactive Infra. (DT-TI)	DT-TI1	0.844	0.023	36.696	0.822	0.894	0.738
	DT-TI2	0.881	0.018	48.944			
	DT-TI3	0.852	0.022	38.727			
Internal Integration (SCI-II)	SCI-II1	0.792	0.028	28.286	0.858	0.904	0.702
	SCI-II2	0.848	0.022	38.545			
	SCI-II3	0.864	0.020	43.200			
	SCI-II4	0.846	0.022	38.455			
Supplier Integration (SCI-SI)	SCI-SI1	0.816	0.025	32.640	0.874	0.914	0.727
	SCI-SI2	0.868	0.019	45.684			
	SCI-SI3	0.879	0.018	48.833			
	SCI-SI4	0.847	0.022	38.500			
Customer Integration (SCI-CI)	SCI-CI1	0.784	0.029	27.034	0.851	0.900	0.692
	SCI-CI2	0.856	0.021	40.762			
	SCI-CI3	0.854	0.021	40.667			
	SCI-CI4	0.832	0.023	36.174			
Anticipation & Readiness (SCR-AR)	SCR-AR1	0.842	0.023	36.609	0.834	0.901	0.752
	SCR-AR2	0.886	0.017	52.118			
	SCR-AR3	0.873	0.019	45.947			
Absorptive Capacity (SCR-AB)	SCR-AB1	0.831	0.024	34.625	0.812	0.889	0.727
	SCR-AB2	0.874	0.019	46.000			
	SCR-AB3	0.853	0.022	38.773			
Restorative Velocity (SCR-RV)	SCR-RV1	0.865	0.020	43.250	0.841	0.904	0.759
	SCR-RV2	0.896	0.016	56.000			
	SCR-RV3	0.852	0.022	38.727			
Environmental Dynamism (ED)	ED-1	0.818	0.025	32.720	0.816	0.891	0.732
	ED-2	0.872	0.019	45.895			
	ED-3	0.875	0.019	46.053			

B. Discriminant Validity

We verified discriminant validity using both Fornell-Larcker comparisons (Fornell & Larcker, 1981) and the Heterotrait-Monotrait (HTMT) ratio (Henseler et al., 2015). Under Fornell-Larcker, the square root of each construct's AVE exceeded its correlations with any other variable (Table 7). Furthermore, all HTMT values remained safely below the conservative 0.85 threshold (Table 8 and Figure 5). The highest observed ratio occurred between restorative velocity and anticipation/readiness ($HTMT = 0.762$), confirming that each construct captures a distinct operational phenomenon.

Table VII: Fornell-Larcker Criterion Assessment Matrix

Construct	1	2	3	4	5	6	7	8	9	10
1. DT-AC	0.844									
2. DT-VI	0.582	0.850								
3. DT-TI	0.514	0.548	0.859							
4. SCI-II	0.442	0.476	0.491	0.838						
5. SCI-SI	0.468	0.512	0.438	0.528	0.853					
6. SCI-CI	0.418	0.462	0.424	0.486	0.518	0.832				
7. SCR-AR	0.486	0.524	0.452	0.514	0.542	0.476	0.867			
8. SCR-AB	0.452	0.488	0.418	0.482	0.526	0.454	0.612	0.853		
9. SCR-RV	0.474	0.506	0.446	0.498	0.554	0.482	0.638	0.594	0.871	
10. ED (Ctrl)	0.214	0.248	0.186	0.224	0.262	0.198	0.284	0.272	0.296	0.856

Table VIII: Heterotrait-Monotrait Ratio of Correlations (HTMT) Analysis Matrix

Construct	1	2	3	4	5	6	7	8	9	10
1. DT-AC	-									
2. DT-VI	0.669	-								
3. DT-TI	0.608	0.647	-							
4. SCI-II	0.513	0.551	0.584	-						
5. SCI-SI	0.538	0.587	0.516	0.609	-					
6. SCI-CI	0.487	0.536	0.507	0.569	0.601	-				
7. SCR-AR	0.572	0.615	0.546	0.607	0.635	0.564	-			
8. SCR-AB	0.539	0.579	0.511	0.577	0.624	0.543	0.743	-		
9. SCR-RV	0.556	0.593	0.536	0.588	0.647	0.569	0.762	0.718	-	
10. ED (Ctrl)	0.254	0.292	0.228	0.269	0.309	0.237	0.342	0.334	0.358	-

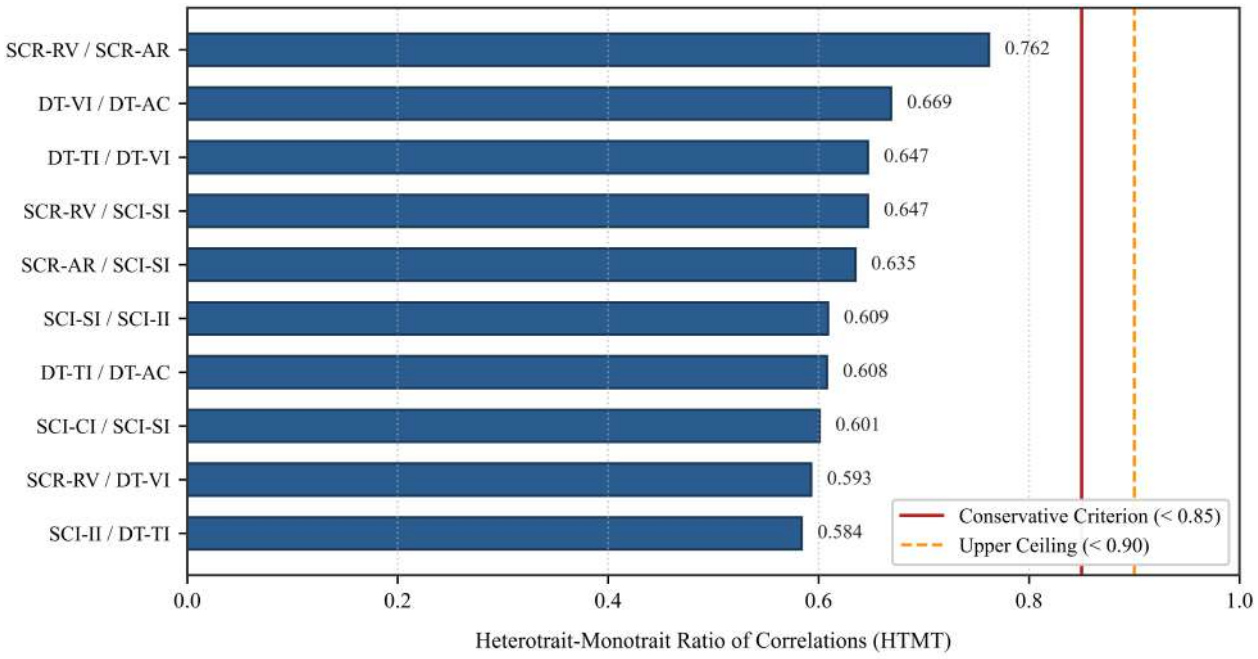

Fig. 5. HTMT discriminant validity compliance profile across construct pairs.

C. Structural Model Evaluation and Hypotheses Testing

We evaluated the structural paths using non-parametric bootstrapping with 5,000 resamples. The model accounts for 52.8% of the total variance in supply chain resilience ($R^2 = 0.528$). Digital investments explained 29.4% of internal integration variance, 31.1% of supplier integration, and 24.4% of customer integration.

The path coefficients confirmed all direct hypotheses (Table 10). Digital transformation directly supports supply chain resilience ($\beta = 0.218$, $t = 3.964$, $p < 0.001$), supporting H_1. Digital tools also strongly drive all three integration vectors: internal integration ($\beta = 0.542$, $p < 0.001$), supplier integration ($\beta = 0.558$, $p < 0.001$), and customer integration ($\beta = 0.494$, $p < 0.001$), confirming H_{2a}, H_{2b}, and H_{2c} with large effect sizes ($f^2 > 0.32$).

In turn, each integration dimension directly bolsters resilience: internal integration ($\beta = 0.204$, $p < 0.001$), supplier integration ($\beta = 0.286$, $p < 0.001$), and customer integration ($\beta = 0.176$, $p = 0.002$), validating H_{3a}, H_{3b}, and H_{3c}. Among the control variables, environmental dynamism had a small, significant positive relationship with resilience effort ($\beta = 0.138$, $p = 0.008$), while firm size, firm age, and geographic dispersion showed no significant influence.

Table IX: Second-Order Construct Validation: Digital Transformation (DT)

First-Order Latent Dimension	Higher-Order Loading (gamma)	SE	t-statistic	p-value	First-Order R2
Analytical Capabilities (DT-AC)	0.838	0.022	38.091	< 0.001	0.702
Real-Time Visibility (DT-VI)	0.862	0.019	45.368	< 0.001	0.743
Transactive Infrastructure (DT-TI)	0.814	0.026	31.308	< 0.001	0.663

D. Mediation Analysis

We evaluated the indirect paths using bias-corrected bootstrap confidence intervals (Table XI). All three indirect pathways proved statistically significant:

(1) Digital transformation → internal integration → resilience ($\beta = 0.111$,95% CI $[0.050,0.178]$, $p = 0.001$)

(2) Digital transformation → supplier integration → resilience ($\beta = 0.160$,95% CI $[0.092,0.236]$, $p < 0.001$)

(3) Digital transformation → customer integration → resilience ($\beta = 0.087$,95% CI $[0.034,0.150]$, $p = 0.004$)

The total indirect effect mediated through supply chain integration ($\beta = 0.358, p < 0.001$) notably exceeds the standalone direct effect ($\beta = 0.218$). Because both the direct and indirect paths remain positive and significant, our data confirms a complementary partial mediation model across all three dimensions, supporting H4a, H4b, and H4c.

Table X: Structural Model Assessment and Direct Path Hypotheses Results

Path / Hypothesis	Coeff (beta)	SE	t-statistic	p-value	95% BCa CI	f2	Decision
H1: DT -> SCRes	0.218	0.055	3.964	< 0.001	[0.110, 0.324]	0.068	Supported
H2a: DT -> SCI-II	0.542	0.048	11.292	< 0.001	[0.446, 0.632]	0.416	Supported
H2b: DT -> SCI-SI	0.558	0.047	11.872	< 0.001	[0.462, 0.648]	0.452	Supported
H2c: DT -> SCI-CI	0.494	0.050	9.880	< 0.001	[0.392, 0.588]	0.322	Supported
H3a: SCI-II -> SCRes	0.204	0.056	3.643	< 0.001	[0.094, 0.312]	0.056	Supported
H3b: SCI-SI -> SCRes	0.286	0.058	4.931	< 0.001	[0.172, 0.398]	0.104	Supported
H3c: SCI-CI -> SCRes	0.176	0.056	3.143	0.002	[0.068, 0.286]	0.042	Supported
Firm Size -> SCRes	0.082	0.048	1.718	0.086	[-0.012, 0.174]	0.011	Non-significant
Firm Age -> SCRes	-0.034	0.046	0.736	0.462	[-0.124, 0.056]	0.002	Non-significant
SC Geo. Disp. -> SCRes	-0.068	0.047	1.447	0.148	[-0.158, 0.024]	0.008	Non-significant
Env. Dynamism -> SCRes	0.138	0.052	2.654	0.008	[0.036, 0.238]	0.031	Significant

Bootstrapped mediation analysis demonstrated that the indirect effect of DT via supply chain integration (beta = 0.358, p < 0.001) is substantial and exceeds the standalone direct effect (beta = 0.218), establishing complementary partial mediation (H4a-c).

Table XI: Indirect Mediation Effects Analysis via Bootstrapping (N = 284)

Mediation Path / Hypothesis	Indirect (beta)	SE	t-statistic	p-value	95% BCa CI	Mediation Type
H4a: DT -> SCI-II -> SCRes	0.111	0.033	3.364	0.001	[0.050, 0.178]	Complementary Partial
H4b: DT -> SCI-SI -> SCRes	0.160	0.037	4.324	< 0.001	[0.092, 0.236]	Complementary Partial
H4c: DT -> SCI-CI -> SCRes	0.087	0.030	2.900	0.004	[0.034, 0.150]	Complementary Partial
Total Indirect Effect	0.358	0.050	7.160	< 0.001	[0.262, 0.458]	-
Direct Effect (H1)	0.218	0.055	3.964	< 0.001	[0.110, 0.324]	-
Total Effect (DT -> SCRes)	0.576	0.046	12.522	< 0.001	[0.482, 0.664]	-

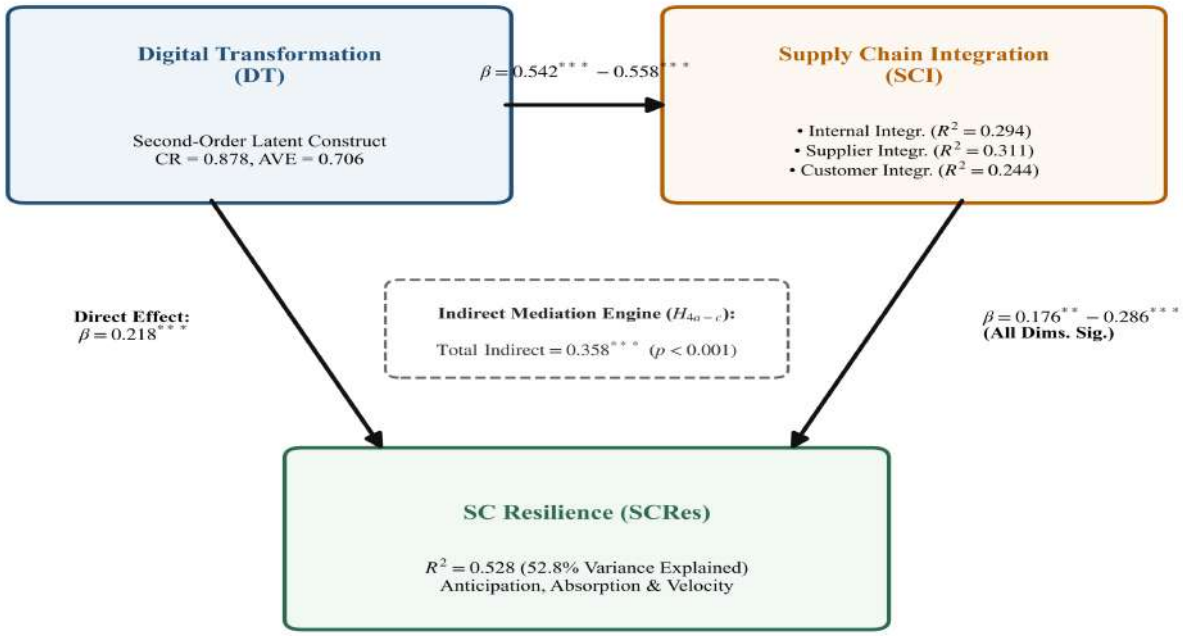

Fig. 6. Validated structural model with standardized path coefficients and variance explained.

V. DISCUSSION AND IMPLICATIONS

A. Discussion of Empirical Findings

Our data offers a clear statistical picture of how manufacturers survive environmental shocks. First, digital transformation directly supports resilience ($\beta = 0.218, p < 0.001$), supporting H_1 . Predictive analytics, cloud infrastructure, and transit sensors shorten the delay between early storm warnings and managerial decisions on the floor. Second, digital investments strongly drive all three integration dimensions (H_{2a}–H_{2c}), producing large effect sizes ($f^2 > 0.32$) . Standard APIs, unified cloud databases, and automated cargo alerts cut through administrative friction and break down information silos. Third, internal, supplier, and customer integration all directly improve resilience (H_{3a}–H_{3c}) . Among these, supplier integration exerts the strongest individual pull ($\beta = 0.286$) . When severe storms take out primary component suppliers, pre-arranged capacity sharing and shared buffer stock keep production lines running.

The mediation analysis (H_{4a}–H_{4c}) gets straight to the heart of the digital paradox. The combined indirect path through supply chain integration ($\beta = 0.358$) is considerably larger than the direct link from digital tools ($\beta = 0.218$) . This explains why standalone tech deployments so often disappoint. Dashboards tell managers what is about to fail, but joint planning with suppliers and customers moves inventory around the bottleneck.

B. Theoretical Implications

These findings advance operations management literature in three specific ways. First, we clarify the mechanics behind the digital paradox during physical disruptions. We demonstrate complementary partial mediation: digital tools without supply chain integration produce expensive surveillance networks that record plant shutdowns in real time without stopping them.

Second, we tie Information Processing Theory directly to Dynamic Capabilities. IPT explains the volume and speed of operational information, while DCV describes how organizations alter their routines. They align as a clear operational sequence: digital systems

provide the *sensing* capacity, cross-enterprise integration handles the *seizing* through mutual contingency agreements, and the resulting *reconfiguration* appears as operational resilience faster recovery times, protected capacity, and minimal downtime.

Third, disaggregating integration shows that not all collaborative paths do the same work. Upstream supplier integration functions as the primary operational shock absorber during raw material shortfalls. Internal integration keeps internal departments from working at cross-purposes, and customer integration prevents panicked double-ordering and bullwhip effects during freight delays.

C. Managerial and Practical Implications

For supply chain directors, plant managers, and software architects, these results point to three clear priorities:

(a) Stop buying standalone visibility software: Purchasing satellite trackers or predictive disruption software without connecting those tools to supplier systems creates little operational value. Technology budgets must include funding for joint onboarding and data sharing across supplier tiers.

(b) Put supplier collaboration first: Because upstream supplier integration has the strongest impact on resilience, firms should focus digital spending on suppliers first. Useful steps include shared safety-stock monitors, pre-negotiated capacity reservations, and standard API connections that automate backup purchase orders when weather halts primary routes.

(c) Clean up internal ERP data before going externally: Internal integration sets the baseline for external cooperation. Procurement, warehouse, and production planning teams must operate on a single internal system before a company attempts to coordinate contingency responses with external partners.

VI. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

A. Conclusion

We evaluated how digital tools, multi-tier integration, and supply chain resilience interact when manufacturers face severe environmental shocks. Using survey responses from 284 industrial plants, our structural model reveals that while digital investments directly improve resilience, their primary value comes through supplier, internal, and customer integration.

This dynamic solves the digital paradox. Algorithmic warnings and IoT sensors help operations teams see problems coming, but without coordinated routines, those signals do not translate into physical recovery. To protect industrial networks against worsening environmental volatility, manufacturing leaders must view digital tools as a foundation for partner collaboration rather than a quick technological fix.

B. Limitations and Future Research Directions

Several limitations in our study open useful avenues for future work. First, our findings rely on cross-sectional survey data. While we ran strict statistical checks to ensure common method bias did not distort the results, cross-sectional surveys cannot track recovery speeds over time. Future research should use multi-year panel datasets or field incident studies to observe how operational buffers degrade and recover during repeat climate events.

Second, our data came from single informants within each focal plant. Although we surveyed senior directors with wide operational oversight, single-firm reporting can miss differences in perspective. Subsequent studies would benefit from matched dyadic or triadic surveys that collect data from focal plant managers, their key suppliers, and their distributors at the same time.

Third, we limited our sample to four physical manufacturing sectors (automotive, process chemicals, electronics, and agribusiness). Service networks, healthcare supply lines, and cold-chain food distributors face different constraints and deserve dedicated study.

Finally, enterprise tools are changing rapidly with the introduction of autonomous software agents and smart contract execution. Future research should investigate whether automated algorithms can handle routine disruption responses on their own, or whether severe physical shocks will always require human relationships and managerial trust to keep supply chains moving.

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