

Digital Transformation, Collaborative Efficiency and Supply Chain Antifragility: A Dual Nonlinear Mediation Model with Curvature Moderation

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Abstract

Supply chain disruptions increasingly expose the inadequacy of resilience-only thinking, yet the mechanisms by which digital transformation (DT) is associated with genuine antifragility—a capacity to improve rather than merely recover—remain poorly understood. Drawing on the too-much-of-a-good-thing framework and organizational learning theory, this paper develops a dual nonlinear mediation model incorporating a direct effect path, two nonlinear mediation paths, and a moderation structure, and tests it on a sample of 350 Chinese manufacturing enterprises (predominantly small and medium-sized). The results show that DT is significantly and positively associated with supply chain antifragility (SCA). Intra-organizational collaborative efficiency exhibits an inverted U-shaped mediating path: beyond a turning point, further increases in internal collaboration are associated with lower SCA. Inter-organizational collaborative efficiency exhibits a U-shaped mediating path: SCA initially declines with rising external collaboration before turning upward, and most sampled firms (60.9%) sit below this trough. Innovation ambidexterity balance moderates both curvatures—it significantly flattens the inverted-U of the internal path (H6), while its flattening of the U-shaped external path remains exploratory (H7). H1–H3, H5, and H6 are supported; H4 receives conditional support—the curvature and rising arm are robust, but the declining arm rests on a thin upper tail (17.1% of firms) and is corroborated by two of three complementary tests; H7 is exploratory rather than confirmed ($p = .050$, achieved power $\approx .50$). The study clarifies when collaboration builds antifragility, when it stops helping, and when it temporarily hurts.

Keywords

Digital Transformation; Supply Chain Antifragility; Collaborative Efficiency; Innovation Ambidexterity; Nonlinear Mediation.

1. Introduction

Existing studies have demonstrated that corporate digital transformation can significantly enhance industrial and supply chain resilience by promoting the completeness of supply chain information transmission and improving supply-demand matching accuracy; digital collaboration can also improve supply chain resilience, with resource integration as a significant mediating channel [1]—providing an empirical foundation for investigating the link between digital transformation (DT) and supply chain antifragility (SCA).

Nevertheless, three gaps remain in the existing literature. First, conceptual confusion: most studies treat resilience merely as a dependent variable and fail to distinguish clearly between 'returning to the original baseline' and 'surpassing the original baseline.' Second, unclear path mechanisms: the specific pathways through which digital transformation (DT) is associated with supply chain antifragility (SCA) via collaborative efficiency have not been systematically revealed. Third, the limitations of linear assumptions: existing mediation models generally

assume that the effect of collaborative efficiency on SCA is monotonically linear, ignoring the possibility that collaboration may yield diminishing-or even sign-reversing-returns at different levels [2]. A telling illustration from our own data motivates this gap: inter-organizational collaborative efficiency is nearly uncorrelated with SCA under a linear lens ($r = 0.04$), yet, as we show, carries a significant U-shaped association that a linear specification would misread as null.

The closest empirical neighbors sharpen the gap. Bag et al. [3] link data-driven DT to antifragility in humanitarian supply chains but model the relationship linearly and in a non-commercial context; Shi et al. [4] and N. Zhao et al. [5] document DT's positive association with supply chain resilience in Chinese manufacturing, likewise under linear specifications and with resilience-not antifragility-as the outcome. The broader digitalization-resilience evidence base [6–8] shares both features; Priyadarshini et al. [9] take antifragility as the outcome but model the enablers of additive-manufacturing implementation with interpretive structural methods (TISM–MICMAC) rather than estimating outcome associations. The present study's increment over this stream is therefore threefold: a nonlinear mediation structure, an antifragility (not resilience) outcome, and a moderation account of when the nonlinearities change shape.

Digital transformation has become the core strategic choice for Chinese enterprises to strengthen their technological innovation capabilities. Its mechanisms acting on supply chain antifragility-a new form of capability-not only advance the theoretical frontier of supply chain management but also profoundly shape the path-dependent characteristics of enterprise technology innovation management. Accordingly, this study asks: through what mechanisms, and under what boundary conditions, is digital transformation associated with supply chain antifragility, and do the two collaboration channels transmit this association linearly or nonlinearly? We address this question with a sample of 350 Chinese manufacturing enterprises (predominantly SMEs), specifying digital transformation as the independent variable, supply chain antifragility as the dependent variable, intra- and inter-organizational collaborative efficiency as two parallel mediating variables, and innovation ambidexterity balance as the moderating variable. Because the data are cross-sectional, all estimated relationships are between-firm associations; we frame dynamic interpretations as hypotheses for future longitudinal research rather than as findings (see Section VI).

2. Theoretical Foundations and Literature Review

2.1. Supply Chain Antifragility: Conceptual Definition and Research Status

Taleb [10] argued that there are three types of responses to external volatility: fragility (becoming weaker after shocks), resilience/robustness (remaining unchanged after shocks), and antifragility (becoming stronger after shocks). Antifragility is not a strengthened version of resilience but a dynamic capability fundamentally different from resilience, whose core characteristic is a 'positive feedback mechanism fueled by volatility.'

In the supply chain domain, Nikookar et al. [11] define SCA as 'a supply chain system capable of withstanding external disruptions while learning, adapting, and improving its own performance from those disruptions.' Related work has also begun to examine antifragility in collaborative business networks [12]. Building on Nikookar et al.'s [13] capability blueprint-which explicitly leaves operationalization to future research-this study measures SCA through dimensions such as post-crisis capability gains, learning from uncertainty, and proactive stress testing.

It is necessary to further clarify the essential distinctions between antifragility and adjacent concepts in supply chain management. Robustness concerns the static capacity of a system to maintain structural integrity when resisting shocks; resilience concerns the dynamic recovery capacity to return to the original state after a shock; antifragility not only achieves 'return to

the original baseline' but also emphasizes 'surpassing the original baseline' by triggering innovative restructuring after shocks, achieving a step-change in capabilities [14]. The differences among the three are not differences of degree but differences of mechanism-triggering conditions and evolutionary paths are entirely different.

Antifragility should also be distinguished from two further neighbors. From the viability stream, a viable supply chain survives structural disruption through reconfigurability-survivability, not improvement, is the criterion [15, 16]; the ripple-effect literature likewise models disruption propagation and containment rather than post-shock gains [17]. And within resilience research itself, the engineering perspective (bounce back to a prior equilibrium) differs from the socio-ecological perspective (adapt and reorganize toward a new state) [18]; antifragility is closer in spirit to the latter but adds the stronger requirement of net gain from volatility [19]. We therefore treat robustness, resilience, viability, and antifragility as mechanism-distinct responses to adversity, and our dependent variable targets only the last.

2.2. Collaborative Efficiency and Supply Chain Antifragility

Supply chain collaborative efficiency refers to the capacity of supply chain participants to coordinate effectively at the levels of information, resources, and decision-making. This study defines intra-organizational collaborative efficiency (M1) as the level at which different functional departments within an enterprise achieve effective coordination in information sharing, goal alignment, and process integration-that is, the level of intra-organizational collaboration; and inter-organizational collaborative efficiency (M2) as the level at which a firm and external stakeholders such as suppliers and customers achieve effective coordination in information sharing and joint decision-making-that is, the level of inter-organizational collaboration [20, 21]. Collaboration creates value through synergy-emergent performance exceeding the sum of individual participants' contributions [20]-but, as we argue below, the marginal value of collaboration need not be monotonic in its level. Digital transformation (DT) refers to a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies [22]; existing research links DT to supply chain capability gains through digital platforms [5] and, in humanitarian settings, to antifragility itself [3].

2.3. Nonlinear Dynamics of Collaborative Efficiency: Theoretical Foundation for the Antifragility Formation Mechanism

That organizational relationships turn nonlinear has a well-established theoretical home that does not require dynamical-systems vocabulary. The too-much-of-a-good-thing (TMGT) framework holds that apparently beneficial antecedents reach inflection points beyond which their effects plateau or reverse, because the very mechanisms that create value at moderate levels generate costs at high levels [2]. Organizational-learning theory supplies the micro-mechanisms for both signs of curvature relevant here: exploitation of refined routines improves reliability but traps organizations in competency traps and core rigidities that suppress adaptive variation [23–25], while adaptation on rugged landscapes implies that over-optimized systems settle into local optima from which incremental improvement cannot escape [26]. Conversely, investments in new inter-organizational linkages have a J-curve cost structure: switching, interface-integration, and trust-building costs are paid upfront, whereas coordination benefits compound only after routines stabilize. Following Dooley and Van de Ven [27], we note that these are claims about nonlinearity-systematically changing marginal effects-not about chaos in the technical sense, and we deliberately frame them as such. Figure 1 summarizes the two resulting path shapes heuristically.

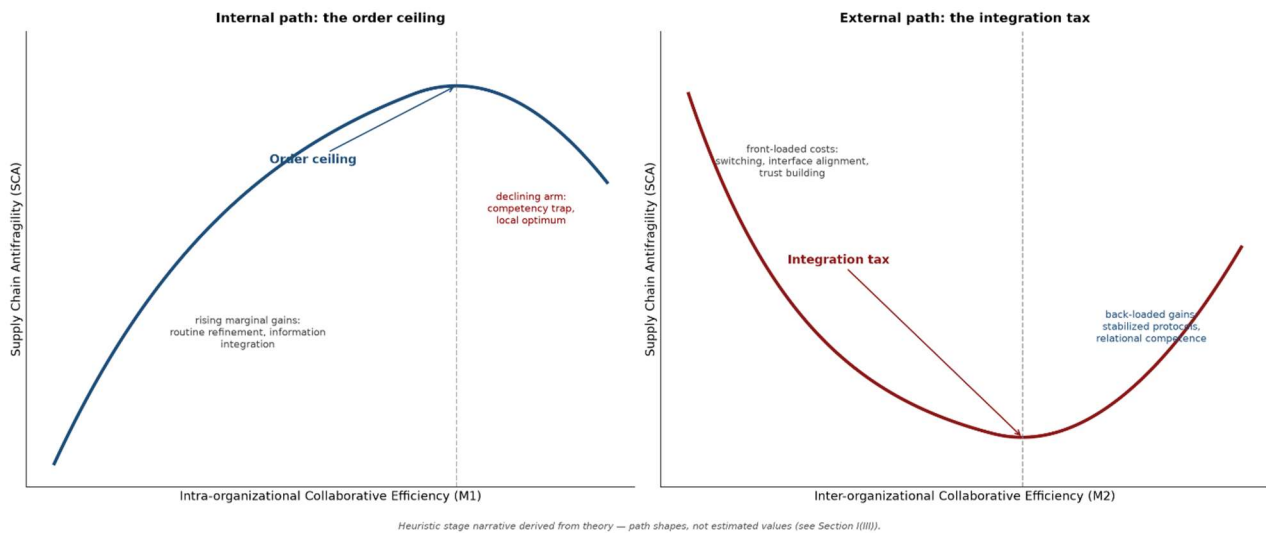


Figure 1. Dual nonlinear paths of collaborative efficiency: the internal order ceiling and the external integration tax (heuristic stage narrative).

Note: the figure depicts theoretical path shapes derived from the literature; it is not estimated from the data, and the cross-sectional design of this study identifies between-firm associations, not within-firm trajectories.

2.4. Ambidexterity Theory and Innovation Balance

Ambidexterity theory emphasizes that high-performing organizations tend to sustain a balance between two strategic orientations: exploitative and exploratory innovation. This study treats innovation ambidexterity balance (W) as the degree of equilibrium a firm maintains between exploitative and exploratory innovation [25, 28]. We follow Cao, Gedajlovic, and Zhang [29] in distinguishing the balanced dimension of ambidexterity (proximity to equality between the two orientations) from its combined dimension (their joint magnitude), and operationalize the balanced dimension as $W = 1 - |\text{EXP} - \text{EXR}| / 4$. Two known limitations of this operationalization—a firm low on both orientations scores as 'balanced' as one high on both, and difference-based scores inherit reliability penalties [30]—are addressed through combined-dimension covariate controls and multiplicative-measure robustness checks in Section IV(V) (see also [31]). At the leadership level, such balance is sustained by enabling-leadership practices that shield adaptive work from standardization pressures while holding exploitation routines accountable [32].

3. Research Model and Hypothesis Development

3.1. Research Model Overview

This study uses digital transformation (DT) as the independent variable, supply chain antifragility (SCA) as the dependent variable, intra-organizational collaborative efficiency (M1) and inter-organizational collaborative efficiency (M2) as two parallel nonlinear mediation paths, and innovation ambidexterity balance (W) as the moderating variable, advancing a total of seven hypotheses (see Figure 2). M1 is hypothesized to mediate the DT–SCA association in an inverted-U shape, M2 in a U-shape, and W to moderate the curvature of both paths (flattening each).

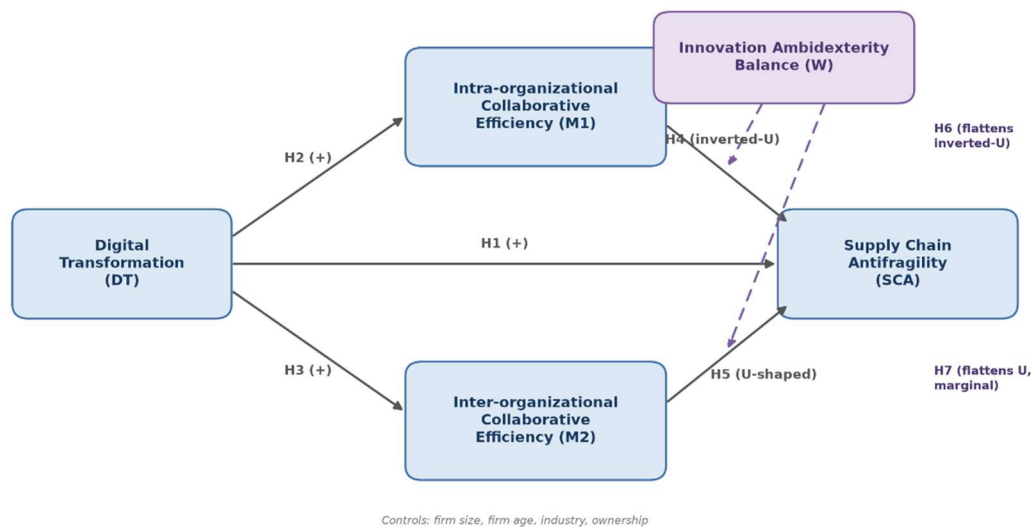


Figure 2. Theoretical Model of Digital Transformation's Associations with Supply Chain Antifragility

3.2. Direct Effects and Antecedent Mediation Hypotheses

Digital transformation is expected to be directly and positively associated with supply chain antifragility through three mechanisms: visibility improvement, intelligent decision-making, and ecosystem reconstruction. Meanwhile, DT should raise intra-organizational collaborative efficiency (M1) by eliminating information silos via ERP/MES systems, and raise inter-organizational collaborative efficiency (M2) through real-time information sharing enabled by digital platforms [4, 33].

H1: Digital transformation is positively associated with supply chain antifragility ($\beta > 0$).

H2: Digital transformation is positively associated with intra-organizational collaborative efficiency ($\beta > 0$).

H3: Digital transformation is positively associated with inter-organizational collaborative efficiency ($\beta > 0$).

3.3. Nonlinear Mediation Hypotheses

The association between collaborative efficiency and SCA is unlikely to be monotonic; we argue it changes sign at different collaboration levels, for mechanism-level reasons that differ between the two collaboration channels.

Intra-organizational collaborative efficiency (M1). At low-to-moderate M1, cross-departmental information sharing and goal alignment allow the organization to integrate internal resources rapidly when disruptions hit; the resulting capability gains from disorder are the hallmark of antifragility [11]. As M1 rises further, however, the same refinement of routines that produces reliability begins to generate its classic pathologies: structural inertia and competency traps, in which entrenched routines crowd out the variation needed for adaptation [23, 25, 34]; core rigidities, in which deeply embedded coordination routines become constraints on novel responses [24]; and settlement into local optima, in which a highly optimized internal system loses the variation needed to improve through shocks [26]. Internal collaboration is particularly exposed to these pathologies because it lacks an exit option—departments cannot leave the firm, so over-ordered coordination persists and compounds. This is a textbook TMGT structure [2]: the marginal contribution of internal collaboration to SCA should decline and eventually turn negative. Hence:

H4: Intra-organizational collaborative efficiency mediates the relationship between digital transformation and supply chain antifragility in an inverted-U shape (linear coefficient > 0 ,

quadratic coefficient < 0), with the declining arm carried by the minority of firms operating beyond the order ceiling.

Inter-organizational collaborative efficiency (M2). External collaboration has the opposite cost timing. Deepening data sharing, joint planning, and system integration with suppliers and customers requires upfront investments-interface and standard alignment, joint emergency-plan development, and trust building across organizational boundaries-whose costs are incurred before coordination benefits materialize; early-stage integration can also disrupt established routines, temporarily degrading disruption response. Because external partners, unlike internal departments, can exit, firms must pay these switching and assurance costs before reciprocal commitment stabilizes. Once integration matures, however, relational competencies strengthen the network's capacity to respond to disruptions [35], and the marginal association with SCA turns positive. The M2 path therefore follows a U-shape-an integration-tax structure in which costs are front-loaded and gains back-loaded.

This prediction must be distinguished from the closest nonlinearity precedent in the collaboration literature. Villena, Revilla, and Choi [36] found an inverted-U between buyer-supplier social capital and performance: relational embeddedness is an asset whose marginal value decays into lock-in and obsolescence at high levels. Collaborative efficiency, as we conceptualize it following Cao and Zhang [20], is not a relational asset but a process capability-the quality of coordination routines. Relational assets depreciate into rigidity as they accumulate (hence Villena et al.'s [36] inverted-U); coordination capabilities are costly to build but compound once installed (hence our predicted U). The two findings are thus complementary rather than contradictory, and together they map the boundary conditions of nonlinearity in inter-organizational relationships. Hence:

H5: Inter-organizational collaborative efficiency mediates the relationship between digital transformation and supply chain antifragility in a U-shape (linear coefficient < 0 , quadratic coefficient > 0).

3.4. Moderation Hypotheses

Innovation ambidexterity balance should moderate the curvature of both paths rather than their level. On the M1 path, exploratory innovation functions as long-jump search that periodically destabilizes over-refined routines [26]: firms that sustain exploration alongside exploitation retain adaptive variation even at high internal-collaboration levels, which should delay the onset of competency-trap pathologies and thus flatten the inverted-U (attenuate its negative quadratic term). On the M2 path, ambidextrous firms possess broader cognitive repertoires and trial-and-error learning capacity [25], which should absorb part of the integration tax-interface conflicts and norm misalignment are more tolerable to organizations accustomed to managing competing innovation agendas-likewise flattening the U-shape (attenuating its positive quadratic term). We emphasize that these are curvature-moderation claims, and we deliberately separate them from any level effect. Sustaining exploration alongside exploitation disperses scarce managerial attention and resources across competing innovation agendas and forces repeated switching between divergent and convergent operating modes [25]; because these friction costs are incurred in the current period, whereas the adaptive benefits of balance materialize only when the collaboration system approaches its limits, we expect the direct (level) effect of balance on SCA to be null to negative in the short run. The contribution of balance therefore lies in changing the shape of the collaboration-SCA relationship, not in raising its level.

H6: Innovation ambidexterity balance moderates the inverted-U relationship between intra-organizational collaborative efficiency and supply chain antifragility, such that higher balance attenuates (flattens) the negative curvature ($W \times M1^2 > 0$).

H7: Innovation ambidexterity balance moderates the U-shaped relationship between inter-organizational collaborative efficiency and supply chain antifragility, such that higher balance attenuates (flattens) the positive curvature ($W \times M2^2 < 0$).

4. Research Methodology

4.1. Sample and Data Collection

This study surveyed Chinese manufacturing enterprises, predominantly small and medium-sized (85.7% with 100–2,000 employees). A total of 550 questionnaires were distributed to manufacturing enterprises in the Yangtze River Delta (40%), Pearl River Delta (30%), Beijing-Tianjin-Hebei region (20%), and other regions (10%) via the Wenjuanxing platform, yielding 350 usable responses (usable rate: 63.6% of distributed questionnaires). All 550 distributed questionnaires were returned; 200 were excluded for excessively short completion time or patterned (straight-line) responding. No additional tenure- or involvement-based informant screening was applied; the respondent position distribution is reported below, and the resulting informant-quality limitation is addressed in Section VI. An early/late respondent comparison (Armstrong–Overton, by response order) showed no significant differences on any study variable (all $p > .09$), mitigating non-response bias concerns. To reduce common method bias (CMB), three procedural measures were adopted: (1) differential time referents-distinct recall frames were applied across construct modules ('over the past three years' for DT/SCA vs. 'current operational status' for M1/M2) within the single-wave instrument; (2) psychological separation-each construct module was introduced with distinct instructions and time referents to reduce respondents' motivation to infer causal relationships among the measures; and (3) a marker variable (job environment satisfaction) was embedded, with Richardson et al.'s [37] statistical correction method applied. Control variables included enterprise size (ln employees), firm age, industry type (dummy variables), and ownership type. Middle managers constituted the primary respondent group (40.0%); detailed information on position level, enterprise size, and industry distribution is presented in Table 1.

4.2. Variable Measurement

All constructs were measured on five-point Likert scales (1 = strongly disagree, 5 = strongly agree). Because validated scales for several focal constructs were unavailable in the Chinese manufacturing SME context, measures were developed or adapted for this study: item pools were generated from the defining literature and refined for the Chinese manufacturing context. We report transparently that no formal expert-content review or pilot test was conducted for the self-developed scales; this is acknowledged as a limitation (Section VI). The complete item list is provided in Appendix A.

Digital Transformation (DT). Five items were developed based on Vial's [22] definition of digital transformation as a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies. The items cover technology deployment (industrial IoT), data utilization (big-data analytics, AI), end-to-end process integration, and strategic commitment, with the time referent set as progress over the past three years. We acknowledge that these items emphasize technology deployment and strategic commitment-closer to digitalization and digital-transformation investment in Verhoef et al.'s [38] staging than to completed business-model transformation-and interpret the construct accordingly.

Intra-organizational Collaborative Efficiency (M1). Five items were adapted from the supply chain collaboration scales of Cao and Zhang [20] and Zhang and Cao [21], recontextualized from the inter-organizational to the intra-organizational setting: real-time information sharing, coordinated response to disruptions, cross-departmental goal alignment,

and decision-process clarity. The time referent was current operational status. One item (M1_5) is a retrospective change item ('compared with three years ago...'); we report reliabilities and model results with and without this item (Section IV(IV)).

Inter-organizational Collaborative Efficiency (M2). Five items were adapted from Cao and Zhang [20] and Zhang and Cao [21], covering data sharing with suppliers, goal and standard alignment, joint emergency planning, and digital system integration with supply chain partners. The time referent was current operational status. One item (M2_5) is a retrospective change item that references improved disruption-handling capability; we report reliabilities and model results with and without this item (Section IV(IV)).

Innovation Ambidexterity Balance (W). Exploitative innovation (EXP) and exploratory innovation (EXR) were each measured with three items adapted from He and Wong [39], contextualized to supply chain capability development ($\alpha = .770$ and $.768$ for EXP and EXR, respectively; $r(\text{EXP}, \text{EXR}) = -.028$). The near-zero correlation is consistent with He and Wong's [39] original finding and plausibly reflects the distinct budget lines and process ownership of incremental versus radical supply chain initiatives in our context; it is also the empirical precondition for the balanced dimension to vary independently of the combined dimension [29]. Following Cao et al. [29], ambidexterity balance was computed as $W = 1 - |\text{EXP} - \text{EXR}| / 4$, with higher values indicating a more balanced innovation orientation; the combined dimension is controlled and a multiplicative alternative examined as robustness (Section IV(V)).

Supply Chain Antifragility (SCA). Six items were developed for this study following the conceptualizations of Taleb [10] and Nikoogar et al. [11, 13]. The items operationalize the defining characteristic of antifragility-becoming stronger after shocks rather than merely recovering to the original baseline-through post-disruption capability gains, systematic learning from crises, conversion of external pressure into opportunity, relative growth during crises, and proactive stress-testing culture. The time referent was actual performance after disruptions experienced over the past three years. We note two measurement features transparently. First, the six items mix outcome-oriented content (SCA1, SCA4, SCA6) with practice/antecedent-oriented content (SCA2, SCA3, SCA5). Three analyses support treating them as one reflective construct: a one-factor CFA of the six items fits well ($\chi^2(9) = 13.65$, CFI = 0.995, TLI = 0.991, RMSEA = 0.038); splitting the items into outcome and practice factors does not improve fit ($\Delta\chi^2(1) = 1.28$, ns) and the two factors correlate at unity ($r \approx 1.0$), indicating empirical indistinguishability; and a bifactor model attributes nearly all reliable item variance to the general factor (general-factor loadings 0.69–0.77; specific-factor loadings $\leq |0.28|$). We additionally report all key models separately for the two subscales as a sensitivity analysis (Section IV(IV)). Second, because the instrument contains no resilience scale, we make no discriminant-validity claim against resilience measures; criterion validity of the scale against objective post-disruption performance awaits multi-source replication (Section VI).

Marker Variable. Three items on workplace environment satisfaction—a construct theoretically unrelated to the substantive variables—were embedded for common method bias diagnosis [37].

4.3. Analytical Methods

Reliability and validity testing employed Stata (sem) for confirmatory factor analysis (CFA), separately assessing AVE, convergent validity (standardized loadings ≥ 0.60 , with the majority exceeding 0.70 [40]), and discriminant validity (Fornell-Larcker criterion). Prior to constructing quadratic and interaction terms, all predictor variables (DT, M1, M2, W) were mean-centered following Haans et al. [41] to reduce multicollinearity and facilitate interpretable coefficient estimates. The nonlinear relationships were tested following the three-condition procedure of Haans et al. [41]: a significant quadratic term with the hypothesized sign, significant and opposite-signed slopes at both ends of the observed data

range, and a turning point located within that range; turning points were calculated via differentiation. Because a nonlinear b-path implies that the indirect effect varies with the mediator level, conditional (instantaneous) indirect effects $\theta = a \times (b_1 + 2b_2 \cdot M)$ were quantified at the mean and ± 1 SD of each mediator [42], with 95% bootstrap confidence intervals obtained from 5,000 resamples. In addition to the three-condition procedure, we apply the Lind and Mehlum [43] intersection-union test of endpoint slopes and Simonsohn's [44] two-lines test as complementary robustness checks for U-shaped hypotheses, report bootstrap 95% confidence intervals for both turning points and for the hypothesized turning-point shift under moderation, and report a sensitivity power analysis for the quadratic and interaction terms. All analyses were conducted in Stata 18 and Python 3 (statsmodels); bootstrap intervals are percentile intervals. No missing data occurred (the survey platform required complete responses before submission); listwise deletion was therefore not needed. Residual diagnostics for Model 3 showed no departure from normality (Jarque-Bera = 1.54, $p = .464$) and mild heteroscedasticity (Breusch-Pagan LM = 26.67, $p = .032$); the HC3 robust-standard-error check reported in Section IV(IV) addresses the latter.

5. Empirical Results

This study tests the hypotheses using a sample of Chinese manufacturing SMEs, organized around the nonlinear mediation-moderation model shown in Figure 2.

5.1. Sample Characteristics and Common Method Bias Test

The usable sample comprised 350 responses (usable rate: 63.6%). Respondents were predominantly middle managers (40.0%), with senior and frontline managers accounting for 16.6% and 25.7%, respectively. Enterprise size was concentrated in the 100-500 employee range (42.6%) and 501-1,000 employee range (25.4%). The sample covered multiple manufacturing sub-industries, including electronics/semiconductors (22.0%) and automotive and components (18.6%); detailed sample characteristics are presented in Table 1.

As a preliminary diagnostic-while Podsakoff et al. [45] caution that the Harman single-factor test has limited standalone validity-the maximum common factor variance was only 23.91% (well below the conventional 50% threshold). A CFA competing-model comparison further demonstrated that the six-factor baseline model fit well ($\chi^2/df = 1.09$, CFI = 0.992, TLI = 0.991, RMSEA = 0.016, 90% CI [0.000, 0.027], SRMR = 0.042), while the fit of a three-factor model-merging the three digital-innovation constructs (DT, EXP, EXR), the two collaboration constructs (M1, M2), and SCA-and a single-factor model deteriorated sharply (Table 2). The marker variable ($\alpha = .712$) was near-orthogonal to the substantive composites ($|r| \leq 0.09$); partialing it out changes no substantive correlation by more than 0.005, and all hypothesis-relevant correlations retain their sign and significance (full marker-adjusted matrix in Appendix B). A latent method factor (ULMC) model estimated as a further sensitivity check improved fit modestly ($\Delta\chi^2(27) = 59.0$) with an average squared method loading of 0.067 (6.7% of item variance; mean $|\lambda| = 0.21$) and all substantive loadings essentially unchanged. These converging checks reduce-but, for a single-source design, cannot eliminate-concerns about common method bias.

Nevertheless, this study must acknowledge the inherent limitation of single-source cross-sectional data: antifragility, collaborative efficiency, and digital transformation were all assessed by the same respondent, and the influence of CMB cannot be fully eliminated through statistical methods alone. In this regard, the three procedural control measures served as proactive countermeasures: differential time reference frames ('over the past three years' vs. 'current operational status') increased the psychological distance between constructs; distinct module instructions and time referents increased the psychological separation between measures; and embedding the marker variable 'job environment satisfaction' provided an

additional statistical correction basis [37]. These measures effectively reduced systematic CMB bias at the procedural level; however, the robustness of the study's conclusions remains to be verified with multi-source data in future research.

Table 1. Sample Demographic Characteristics (N=350)

Variable	Category	Frequency	Percentage
Position Level	Senior Managers	58	16.6%
	Middle Managers	140	40.0%
	Front-line Managers	90	25.7%
	General Staff	62	17.7%
Enterprise Size	<100	23	6.6%
	100-500	149	42.6%
	501-1,000	89	25.4%
	1,001-2,000	62	17.7%
	>2,000	27	7.7%
Years Established	<5 years	69	19.7%
	5-10 years	105	30.0%
	11-20 years	126	36.0%
	>20 years	50	14.3%
Industry	Electronics/Semiconductors	77	22.0%
	Automotive & Components	65	18.6%
	FMCG/Food	53	15.1%
	Medical Devices	53	15.1%
	Machinery/Equipment	55	15.7%
	Other Manufacturing	47	13.4%
Ownership Type	State-owned	81	23.1%
	Private	169	48.3%
	Foreign/JV	78	22.3%
	Other	22	6.3%
IT Investment %	<1%	68	19.4%
	1%-3%	170	48.6%
	3%-5%	77	22.0%
	>5%	35	10.0%
HQ Region	Yangtze River Delta	129	36.9%
	Pearl River Delta	101	28.9%
	Beijing-Tianjin-Hebei	84	24.0%
	Other Regions	36	10.3%

Table 2. Confirmatory Factor Analysis: Competing Model Comparison

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA	SRMR
Six-factor Model (Baseline)	338.02	309	1.09	0.992	0.991	0.016 [0.000, 0.027]	0.042
Three-factor Model (DT+EXP+EXR M1+M2 SCA)	1452.34	321	4.52	0.686	0.656	0.100 [0.095, 0.106]	0.175*
Single-factor Model	2347.26	324	7.24	0.438	0.391	0.134 [0.129, 0.139]	0.185*

Note. RMSEA values in brackets are 90% confidence intervals. *SRMR values for the ill-fitting comparison models are reported for completeness; they are not interpretable as close fit. The three-factor model merges the three digital-innovation constructs (DT, EXP, EXR), the two collaboration constructs (M1, M2), and SCA into three composite factors.

5.2. Reliability and Validity Analysis

The Cronbach's α coefficients for each latent variable ranged from 0.77 to 0.88; composite reliability (CR) ranged from 0.77 to 0.88; standardized factor loadings from the six-factor CFA ranged from 0.67 to 0.77 (mean = 0.72; 19 of 27 items ≥ 0.70); and AVE for each construct exceeded the 0.50 threshold (range 0.50–0.54). Regarding discriminant validity, the square root of each construct's AVE was greater than its correlations with other constructs, satisfying the Fornell-Larcker criterion (see Table 4). Additionally, HTMT ratios for all construct pairs ranged from 0.025 to 0.536 (maximum: DT vs. M1), well below the 0.85 threshold [46], providing further confirmation of discriminant validity.

Table 3. Reliability and Convergent Validity Results

Construct	Items	CFA Std. Loading Range	Cronbach's α	CR	AVE
Digital Transformation (DT)	5	0.666~0.749	0.834	0.835	0.503
Supply Chain Antifragility (SCA)	6	0.683~0.768	0.875	0.875	0.538
Intra-org. Collaborative Efficiency (M1)	5	0.686~0.729	0.839	0.838	0.509
Inter-org. Collaborative Efficiency (M2)	5	0.675~0.758	0.853	0.854	0.540
Exploitative Innovation	3	0.689~0.760	0.770	0.770	0.528
Exploratory Innovation	3	0.667~0.760	0.768	0.769	0.527

5.3. Descriptive Statistics and Correlation Analysis

Table 4. Descriptive Statistics and Correlation Matrix (diagonal: square root of AVE)

Variable	M	SD	1	2	3	4	5
1. Digital Transformation (DT)	3.550	0.527	0.709				
2. Intra-org. Collaboration (M1)	3.693	0.485	0.451***	0.714			
3. Inter-org. Collaboration (M2)	3.493	0.539	0.433***	0.259***	0.735		
4. Supply Chain Antifragility (SCA)	3.527	0.594	0.300***	0.419***	0.040	0.734	
5. Innovation Ambidexterity Balance (W)	0.819	0.131	0.037	0.016	0.013	-0.110*	—

The means and standard deviations of the core variables indicate that the sample enterprises were overall at a moderate stage of digital transformation advancement, with intra- and inter-organizational collaborative efficiency levels broadly matched. DT was significantly positively correlated with both M1 ($r = 0.45, p < 0.01$) and M2 ($r = 0.43, p < 0.01$), providing preliminary support for H2 and H3. M1 was significantly positively correlated with SCA ($r = 0.42, p < 0.01$), while M2's correlation with SCA was non-significant ($r = 0.04, p > 0.05$), suggesting that the effect of M2 on SCA may exhibit nonlinear characteristics; see Table 4 for details.

5.4. Nonlinear Main Effects and Mediation Tests (H1-H5)

The hierarchical polynomial regression results are presented in Table 5. Adding the quadratic terms significantly improved explanatory power (Model 2 $R^2 = 0.249$; Model 3 $R^2 = 0.341$; $\Delta R^2 = 0.092$, $F(2, 334) = 23.22, p < 0.001$), confirming the nonlinear structure; all variance inflation factors were below 1.65 (maximum = 1.63), ruling out multicollinearity. Following Haans et al. [41], all three conditions for the hypothesized curves were verified (Table 6): the quadratic terms are significant with the hypothesized signs; the turning points ($M1 = 4.18$; $M2 = 3.70$) lie within the observed data ranges ($M1: 2.60\text{--}5.00$; $M2: 1.80\text{--}5.00$); and the slopes at both ends of each range are significant with opposite signs. H1 was supported: DT retains a significant positive direct effect on SCA after both mediators and quadratic terms are entered ($\beta = 0.167, p = 0.002$). The antecedent paths were likewise strong: DT positively predicts intra-organizational collaborative efficiency ($\beta = 0.441, p < 0.001$, H2) and inter-organizational collaborative efficiency ($\beta = 0.449, p < 0.001$, H3).

Table 5. Hierarchical Polynomial Regression Results (Dependent Variable: Supply Chain Antifragility; Standardized Coefficients, $N = 350$)

Variable	Model 1	Model 2	Model 3
Digital Transformation (DT)	0.280***	0.173**	0.167**
Intra-org. Collaboration (M1)		0.376***	0.384***
$M1^2$			-0.254***
Inter-org. Collaboration (M2)		-0.131*	-0.116*
$M2^2$			0.200***
$\ln(\text{employees})$	0.105*	0.084	0.065
Firm age	-0.096	-0.099*	-0.098*
Industry dummies	included	included	included
Ownership dummies	included	included	included
R^2	0.133	0.249	0.341
Adjusted R^2	0.104	0.220	0.311
ΔR^2		0.116***	0.092***

Note: * $p < .05$, ** $p < .01$, *** $p < .001$. Industry and ownership dummy coefficients are reported in Appendix B. All continuous predictors are mean-centered; coefficients are standardized. Model 1 adds DT to a controls-only baseline ($R^2 = 0.057$; see Table B2); ΔR^2 for Model 1 versus baseline = 0.076, $p < .001$.

Table 6. U-shape Verification: Slope Tests at Data Range Endpoints and Turning Points

Path	Slope at low end	Slope at high end	Turning point	Data range
M1 → SCA (inverted-U)	1.518*** (t = 7.53)	-0.781*** (t = -3.34)	4.18 [4.02, 4.55]	2.60–5.00
M2 → SCA (U-shape)	-1.165*** (t = -4.86)	0.794*** (t = 3.71)	3.70 [3.51, 4.06]	1.80–5.00

Note. Slopes are unstandardized (raw Likert metric); t-values in parentheses. Turning-point 95% bootstrap CIs (2,000 resamples): M1 [4.02, 4.55]; M2 [3.51, 4.06]. Observations beyond the turning point: M1—60 of 350 firms (17.1%) above the vertex; M2—213 of 350 (60.9%) below the trough. Turning points are computed as $-B_{\text{linear}} / (2 \times B_{\text{quadratic}})$ from the Model 3 unstandardized coefficients.

Turning-point uncertainty and occupancy. Bootstrap 95% CIs (2,000 resamples) place the M1 turning point at 4.184 [4.018, 4.553] and the M2 turning point at 3.703 [3.509, 4.059]. Regarding occupancy of the curvature regions, 60 of 350 firms (17.1%) lie above the M1 vertex (the declining arm), and 213 of 350 (60.9%) lie below the M2 trough—that is, a majority of sampled firms currently sit in the region where external collaboration is negatively associated with SCA, a descriptive fact we return to in the Discussion. The Lind–Mehlum [43] intersection–union test confirms both curves (M1: overall $p = .0005$; M2: $p = .0001$).

Curvature robustness. Simonsohn's [44] two-lines test (subsample regressions split at the quadratic turning point, full controls, two-sided p) strongly supports the M1 rising arm (slope = 0.779, $p < .001$) and the M2 above-trough arm (slope = 0.366, $p = .024$), but not the M1 declining arm (slope = -0.097, $p = .737$) or the M2 below-trough arm (slope = -0.160, $p = .205$). Under Simonsohn's covariate-free Robin Hood knot search, both M2 arms reach significance (below = -0.532, one-sided $p = .007$; above = 0.262, $p = .006$), while the M1 declining arm remains non-significant. The M1 declining arm is further corroborated by the joint spline specification (implied slope above knot = -0.425, slope change $p < .001$) and by the endpoint slope test (-0.781, $p = .0009$). We therefore characterize the M1 downturn as supported by two of three complementary tests and flag its estimation on a thin upper tail (Section VI). The quadratic terms are further robust to: excluding the top decile of M1 ($M1^2 = -0.480$, $p = .004$; $M2^2 = 0.365$, $p < .001$); excluding 20 influential cases (Cook's $D > 4/N$; both $p \leq .001$); HC3 heteroscedasticity-robust standard errors (both $p \leq .001$); excluding general-staff respondents ($n = 288$; both $p \leq .001$); and replacing the mediators with four-item versions excluding the retrospective change items ($M1^2 = -0.429$, $p < .001$; $M2^2 = 0.258$, $p < .001$; turning points 4.17 and 3.68); and adding IT-investment intensity as an additional control (all focal terms unchanged in sign and significance: DT B = 0.145, $p = .022$; $M1^2 = -0.488$ and $M2^2 = 0.305$, both $p < .001$). Full unstandardized coefficient tables (B, SE, β , t, p , 95% CI) for all models appear in Appendix B. The four-item mediator scales retain acceptable reliability (M1: $\alpha = .803$; M2: $\alpha = .825$, vs. .839 and .853 for the five-item versions). Restricting the sample to firms with at most 2,000 estimated employees ($n = 318$, based on the estimated-headcount variable; five firms self-categorized in the 1,001–2,000 band report estimated headcounts marginally above 2,000) leaves both quadratic terms significant ($M1^2 = -0.507$, $p < .001$; $M2^2 = 0.301$, $p < .001$), supporting the SME reading of the results. Finally, a complexity-inspired check on the transition-zone hypothesis—whether SCA variance peaks at intermediate M2—found the opposite pattern: Levene tests across M2 tertiles are significant (Levene's $F(2, 347) = 4.84$, $p = .008$) but variance is lowest in the middle tertile (0.257 vs. 0.454 and 0.365 in the low and high tertiles), and the corresponding test across M1 tertiles is non-significant ($p = .165$). SCA variance is thus highest among firms at low external integration, consistent with heterogeneous early-integration experiences, and affords no support for a variance-peaks-in-transition account.

SCA subscale sensitivity. Separating the SCA scale into outcome-oriented (SCA1, SCA4, SCA6; $\alpha = .773$) and practice-oriented (SCA2, SCA3, SCA5; $\alpha = .770$) subscales ($r = .791$ between them),

both quadratic terms remain significant in both subscale models (all $p \leq .001$), indicating that the nonlinear structure is not an artifact of the item-type mix.

Power. A sensitivity analysis ($\alpha = .05$, power = .80) indicates a minimum detectable increment of $f^2 \approx 0.024$ per term at $N = 350$; both quadratic terms exceed this threshold comfortably. The seven hypotheses were specified a priori as a single confirmatory family with directional predictions; we report exact p values without formal family-wise adjustment and interpret the marginal H7 result with corresponding caution (Section IV(V)).

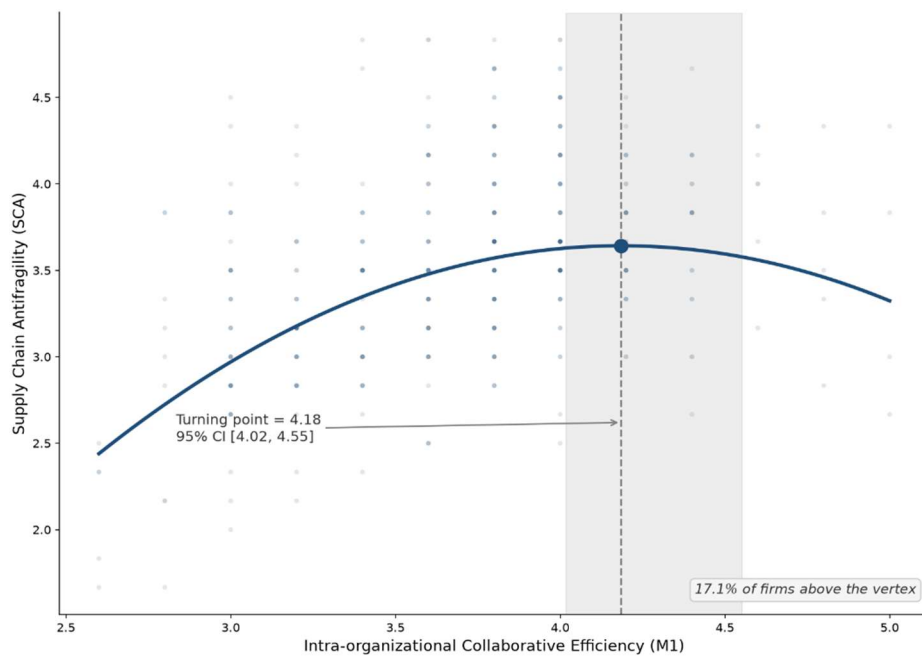


Figure 3. Inverted-U Relationship Between Intra-organizational Collaborative Efficiency and Supply Chain Antifragility

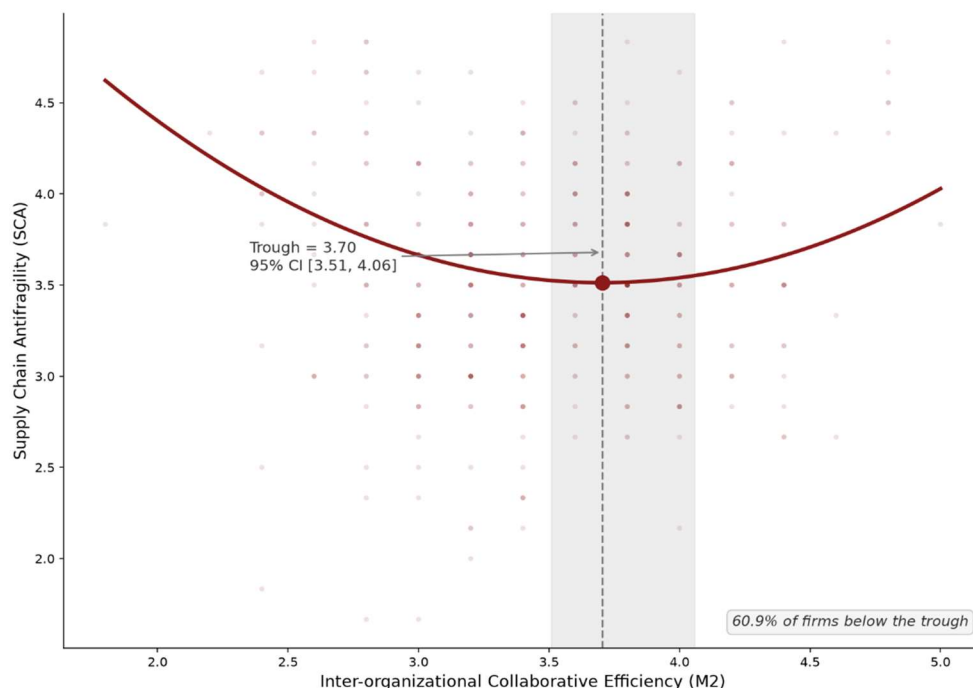


Figure 4. U-shaped Relationship Between Inter-organizational Collaborative Efficiency and Supply Chain Antifragility

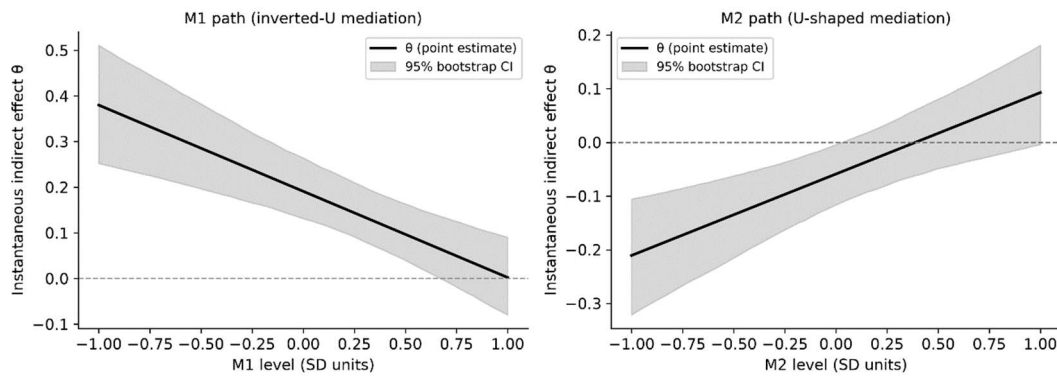


Figure 5. Bootstrap Conditional Indirect Effects of DT→SCA at Different Mediator Levels

Because the b-paths are nonlinear, the indirect effect of DT on SCA varies with the level of the mediator. We therefore quantified the instantaneous indirect effect $\theta = a \times (b_1 + 2b_2 \cdot M)$ [42] at the mean and ± 1 SD of each mediator, with bootstrap confidence intervals (5,000 resamples; Table 7; see also Figure 5). On the M1 path, the indirect effect was significantly positive at low (-1 SD: $\theta = 0.380$, 95% CI [0.252, 0.510]) and mean levels ($\theta = 0.191$, 95% CI [0.130, 0.261]) but vanished at high M1 ($+1$ SD: $\theta = 0.002$, 95% CI [−0.082, 0.090]), confirming the inverted-U mediation pattern (H4). On the M2 path, the indirect effect was significantly negative at -1 SD ($\theta = -0.211$, 95% CI [−0.321, −0.104]) and at the mean ($\theta = -0.059$, 95% CI [−0.116, −0.004]), turning positive (though not yet significant) at $+1$ SD ($\theta = 0.093$, 95% CI [−0.005, 0.183]), confirming the U-shaped mediation structure (H5). We note explicitly that the M2-path indirect effect remains significantly negative or null throughout the sampled mediator range—at M2 = $+1$ SD, $\theta = 0.093$, 95% CI [−0.005, 0.183]—so the positive arm of the U-shape is supported by the curvature and endpoint-slope tests but is extrapolated beyond the levels at which most sampled firms currently operate; 60.9% of firms sit below the trough (see Section IV(IV)).

Table 7. Instantaneous Indirect Effects of DT on SCA at Different Mediator Levels (Bootstrap 5,000 Resamples)

Mediator level	M1 path: θ [95% CI]	M2 path: θ [95% CI]
−1 SD	0.380 [0.252, 0.510]	−0.211 [−0.321, −0.104]
Mean	0.191 [0.130, 0.261]	−0.059 [−0.116, −0.004]
+1 SD	0.002 [−0.082, 0.090]	0.093 [−0.005, 0.183]

5.5. Moderation Effects of Innovation Ambidexterity (H6–H7)

The moderation test results are presented in Table 8. Each model regresses SCA on the focal path (linear and quadratic terms), the non-focal mediator path, DT, W, and the interaction terms, plus all controls (max VIF = 1.83; the interaction block adds $\Delta R^2 = 0.024$, $F(3, 331) = 4.22$, $p = .006$ for H6 and $\Delta R^2 = 0.020$, $F(3, 331) = 3.42$, $p = .018$ for H7 over Model 3). On the M1 path (H6), the $W \times M1^2$ interaction was positive and significant ($B = 1.759$, $SE = 0.738$, $\beta = 0.141$, $p = .018$, 95% CI [0.307, 3.211]): higher ambidexterity balance attenuates the negative curvature of the inverted-U, supporting H6 (Figure 6). We frame this as curvature moderation deliberately: although the point estimate of the conditional vertex moves from $M1 = 4.07$ at low balance (-1 SD) to 4.76 at high balance ($+1$ SD), a bootstrap test shows the shift itself is not statistically distinguishable from zero (95% CI [−0.21, 14.46], the interval being wide because the conditional curvature at high W approaches zero); the defensible claim is that the curve flattens, not that the turning point relocates to a specific value. It is noteworthy that the main effect of W in this model was significantly negative ($\beta = -0.201$, $p < .001$): when the nonlinear effect of M1 is controlled, the exploratory innovation activities of high-ambidexterity firms

appear to be associated with lower SCA in the short run, consistent with the organizational friction and resource dispersion theorized in Section II(IV). The contribution of ambidexterity balance thus lies not in directly raising the SCA level, but in changing the shape of the internal-collaboration path—a trade-off we quantify in the Discussion.

On the M2 path (H7), the $W \times M2^2$ interaction was negative and marginally significant ($B = -1.360$, $SE = 0.692$, $\beta = -0.114$, $p = .050$, 95% CI $[-2.721, 0.000]$): the estimated curvature drops from 0.473 at low balance to 0.116 at high balance. Conditional slope tests show that for low-ambidexterity firms the pronounced U-shape remains (slopes of -1.763 , $p < .001$, and $+1.266$, $p < .001$, at the two ends of the observed M2 range), whereas for high-ambidexterity firms neither endpoint slope is significant (-0.488 , $p = .226$; $+0.253$, $p = .480$). We caution that a non-significant dip under high balance is not evidence of a shortened transition-only of a flatter estimated curve—and that this effect reaches exactly the .05 boundary (achieved power ≈ 0.50 ; Section IV(IV)); we therefore do not count H7 as supported and report it as an exploratory finding: a sensitivity analysis indicates that detecting an interaction of this magnitude ($|t| \approx 1.97$) with 80% power at $\alpha = .05$ (two-tailed) would require approximately $N = 714$.

Robustness of the moderation. Both interactions survive controlling for the combined dimension of ambidexterity—whether operationalized as the mean of EXP and EXR or their product (H6: $p = .018$; H7: $p = .051$)—indicating that the moderation is driven by the balance dimension specifically rather than by the joint magnitude of innovation activity; consistently, a multiplicative operationalization of ambidexterity ($EXP \times EXR$) yields no significant curvature moderation ($p = .531$ and $p = .800$), as the balance-versus-combined-dimension distinction would predict [29]. When general-staff respondents are excluded ($n = 288$), both interaction terms attenuate to marginal significance (H6: $p = .074$; H7: $p = .063$), which we attribute to reduced statistical power rather than to a qualitative change in the estimates (coefficients remain of similar magnitude and sign); we disclose this sensitivity explicitly and interpret H6–H7 with corresponding caution.

Taken together, H1–H3, H5, and H6 were supported, H4 was conditionally supported (robust curvature and rising arm; the declining arm rests on the 17.1% of firms above the vertex and is corroborated by two of three complementary tests), and H7 was not supported at conventional levels and is reported as exploratory: H1 ($\beta = 0.167$, $p = .002$); H2 ($\beta = 0.441$, $p < .001$); H3 ($\beta = 0.449$, $p < .001$); H4 ($\beta_1 = 0.384$, $p < .001$; $\beta_2 = -0.254$, $p < .001$); H5 ($\beta_1 = -0.116$, $p = .020$; $\beta_2 = 0.200$, $p < .001$); H6 ($\beta = 0.141$, $p = .018$); and H7 ($\beta = -0.114$, $p = .050$; achieved power $\approx .50$; $N \approx 714$ required for 80% power).

Table 8. Moderation Effect Tests of Innovation Ambidexterity Balance (Standardized Coefficients)

H6 (M1 Path)	Coefficient	H7 (M2 Path)	Coefficient
Digital Transformation (DT)	0.179***	Digital Transformation (DT)	0.171**
Intra-org. Collaboration (M1)	0.387***	Inter-org. Collaboration (M2)	−0.116*
$M1^2$	−0.233***	$M2^2$	0.192***
Ambidexterity Balance (W)	−0.201***	Ambidexterity Balance (W)	−0.036
$W \times M1$	−0.024	$W \times M2$	0.026
$W \times M1^2$	0.141*	$W \times M2^2$	−0.114†
R^2	0.365	R^2	0.361

Note: † $p = .050$ (marginal; treated as exploratory), * $p < .05$, ** $p < .01$, *** $p < .001$. Each model also includes the non-focal mediator path, DT, W, and all controls (standardized coefficients shown; unstandardized coefficients in Appendix B). Interaction-block increments over Model 3: H6 $\Delta R^2 = 0.024$, $F(3, 331) = 4.22$, $p = .006$; H7 $\Delta R^2 = 0.020$, $F(3, 331) = 3.42$, $p = .018$.

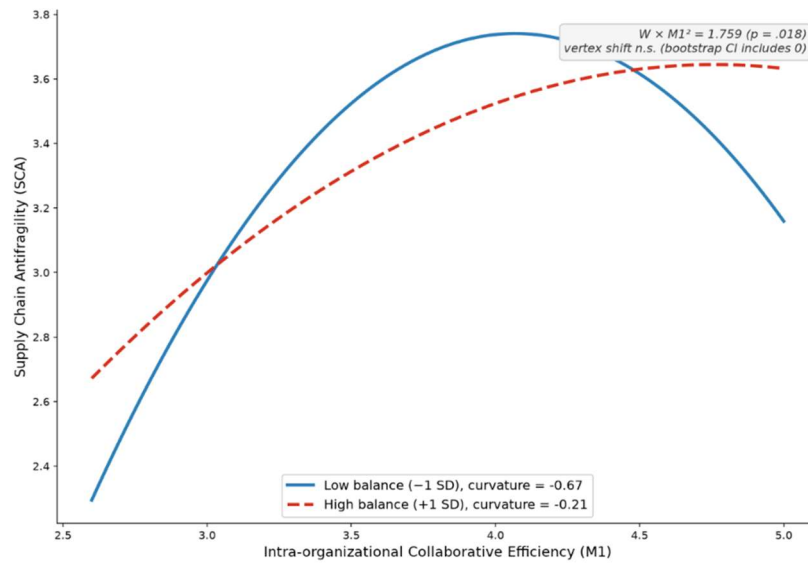


Figure 6. Moderation of the Inverted-U Path (M1) by Ambidexterity Balance (Curvature Flattens at High Balance; Vertex Shift Not Statistically Significant)

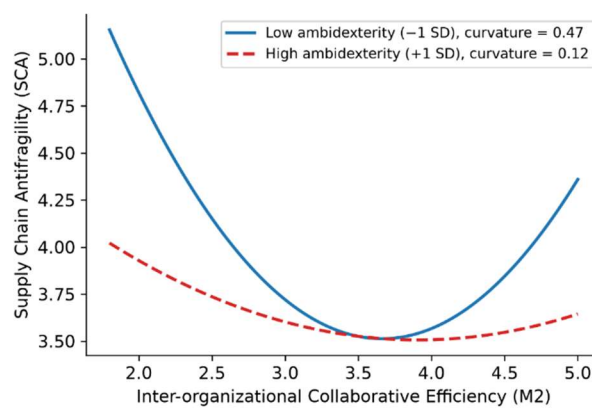


Figure 7. Moderation of the U-shaped Path (M2) by Ambidexterity Balance (Exploratory, $p = .050$)

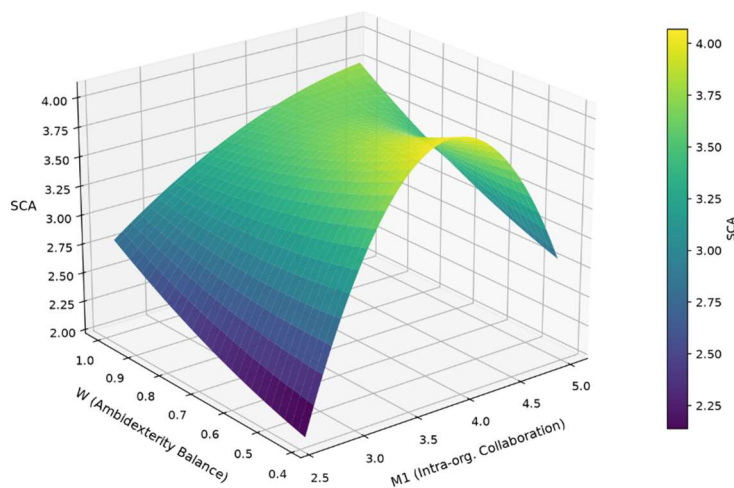


Figure 8. Response Surface of SCA on M1, W, and Their Second-Order Terms (H6 Model Including W^2)

6. Discussion and Theoretical Contributions

6.1. Theoretical Contributions

First, this study advances the empirical operationalization of supply chain antifragility. Existing SCA research has primarily remained at the level of conceptual framework construction [11, 13] or qualitative case analysis. This study is, to our knowledge, among the first to incorporate SCA as a dependent variable into a polynomial regression framework, providing perceptual, self-reported quantitative evidence consistent with the core characteristic of 'surpassing the original baseline after shocks.' We deliberately make no claim of having demarcated SCA from resilience empirically: our instrument contains no resilience scale, and the six-factor CFA establishes discriminant validity only among the constructs we measured. Establishing the SCA–resilience boundary with a jointly administered resilience measure remains a necessary next step (Section VI).

Second, this study reveals mechanism-distinct nonlinear paths through which intra- and inter-organizational collaborative efficiency are associated with SCA. Internal collaboration exhibits an order ceiling: beyond a turning point, further refinement of internal routines is associated with lower antifragility—an inference resting on a significant negative curvature and a robust rising arm, with the declining arm itself carried by the 17.1% of firms beyond the turning point—consistent with competency-trap and local-optimum accounts [23, 26]. External collaboration exhibits an integration tax: deepening inter-organizational coordination is negatively associated with SCA until integration matures, consistent with front-loaded switching and trust-building costs. That the two channels transmit DT's association through opposite-signed curvatures—and that the external channel's U-shape resolves the apparent contradiction with Villena et al.'s [36] inverted-U for relational embeddedness—moves the collaboration literature beyond linear, single-path assumptions [4, 5] and specifies which curvature belongs to which construct and why.

Third, this study identifies 'path curvature moderation' as a novel mechanism of innovation ambidexterity. W does not raise the SCA level—its main effect is significantly negative ($\beta = -0.201$, $p < .001$), a short-term friction cost of exploration—but changes the shape of the DT-linked paths: it significantly flattens the internal inverted-U (H6) and flattens the external U only at the .050 boundary with $\approx .50$ achieved power (H7, exploratory). Ambidexterity balance therefore operates as a structural modifier of how collaboration converts into antifragility, not as a direct performance lever—a trade-off (curvature benefit versus level cost) that extends the balanced-dimension perspective of ambidexterity theory [29] and qualifies simple 'balance is beneficial' prescriptions [31].

Fourth, this study demonstrates the empirical stakes of nonlinear modeling for the DT-supply chain literature. The near-zero linear correlation between M2 and SCA ($r = 0.04$) coexists with a verified U-shaped path: under the linear specifications that dominate this literature, the external-collaboration channel would be dismissed as non-significant. The finding that 60.9% of sampled firms currently sit below the external-integration trough—where collaboration is negatively associated with antifragility—further shows that population composition, not just curve shape, is invisible to linear models. We recast the prevailing conception of 'DT → integration → resilience' as 'DT → heterogeneous nonlinear collaborative paths → SCA.'

6.2. Managerial Implications

First, upgrade from 'building resilience' to 'cultivating antifragility.' DT has an independently significant positive direct association with SCA ($\beta = 0.167$, $p = .002$); managers should upgrade the strategic objective of supply chain digitalization from 'minimizing

disruption losses' to 'transforming disruptions into growth momentum,' investing in the capability to surpass the pre-disruption baseline.

Second, watch for the symptoms of over-ordered internal collaboration. In this sample, the marginal association of internal collaboration with SCA turned negative beyond $M1 \approx 4.2$ on our five-point scale—a value we stress is illustrative of this sample, not a transferable threshold. The transferable content is a diagnostic: falling variance in disruption-response times, a declining share of non-standard responses to exceptions, and lengthening sign-off chains are observable symptoms that internal routines are over-optimized. The countermeasures are structural: protected experimental units, deliberate role rotation, and regular stress-test exercises (the practice our SCA5 item measures) preserve adaptive variation without dismantling coordination.

Third, pre-position for the external-integration tax rather than trying to sprint through it. External collaboration was negatively associated with SCA below the estimated trough ($M2 \approx 3.7$)—a region containing 60.9% of our sample. Because integration costs are front-loaded (interface alignment, joint emergency planning, trust building), the practical lever is sequencing, not speed: standardize data interfaces before deepening joint planning, pre-negotiate emergency protocols before system integration, and stage commitments so that the trough is entered with slack resources. Managers should also expect the transition to be slow-trust and system integration cannot be compressed at will—and should not abandon integration programs mid-trough on the evidence of temporarily deteriorating disruption metrics.

Fourth, manage ambidexterity balance as a structural lever with a short-term price. Balancing exploration with exploitation significantly flattened the internal order ceiling (H6) and showed an exploratory, not yet confirmed flattening of the external integration tax (H7)—but the level effect of balance on SCA was significantly negative ($\beta = -0.201$), meaning exploratory activity is associated with lower antifragility in the short run. For an SME budgeting scarce cash, the honest reading is a trade-off: innovation-balance programs buy a more forgiving collaboration curve at the price of current-period friction. Enabling-leadership practices—shielding adaptive experiments from process standardization while holding exploitation routines accountable—are the managerial mechanism for capturing the former while containing the latter [32].

6.3. Policy Implications

The findings carry three implications for SME digitalization policy, particularly relevant to China's SME digital-transformation pilot programs and 'specialized, refined, distinctive, innovative' cultivation schemes. First, if external integration imposes a transition-period penalty—a region containing a majority of our sampled SMEs—then subsidy designs that reward entering inter-firm digital integration without supporting firms through the trough risk pushing SMEs into a capability dip they cannot afford. Transition-period support instruments (shared integration infrastructure, vouchers that fund mid-integration consolidation rather than initial adoption) target the actual cost structure revealed here. Second, the curvature-moderation results imply that pairing digitalization subsidies with innovation-portfolio support (programs that sustain exploratory capacity alongside exploitation) may soften the transition tax—an actionable program-design combination. Third, the non-monotonic paths caution against evaluating SME digitalization programs on short-horizon KPIs: programs measured during the integration trough will appear to fail precisely when they are paying the upfront costs of later gains. We note that these implications are drawn from a self-selected, regionally concentrated Chinese sample and should be read as program-design hypotheses for policy experimentation rather than as established policy effects.

7. Limitations and Future Research

First, limitations of causal inference from cross-sectional data. This study employed a single-wave cross-sectional questionnaire; cross-sectional data preclude causal inference, and the estimated curves trace between-firm structure, not within-firm trajectories: we cannot determine whether firms pass through the external-integration trough or whether firms observed mid-integration differ systematically from those past it. Future research should employ multi-wave panel designs or quasi-experimental methods (e.g., difference-in-differences exploiting external digital transformation shocks) to establish temporal ordering and to test the dynamic interpretations we have deliberately framed as hypotheses-whether the integration tax is a stage firms transit, whether internal order ceilings bind within firms over time, and whether the path shapes exhibit hysteresis.

Second, sample industry and geographical limitations. Since this study was conducted in China focusing on manufacturing SMEs, the external generalizability of its conclusions requires further verification. Factors specific to the Chinese context-such as ownership structure differences, Guanxi-mediated relational trust, and state-driven digitalization pressure-may condition the depth and duration of the external-integration trough: high-context trust building may deepen or prolong it relative to arm's-length contracting environments, and policy-driven adoption may push firms into integration before they are ready, populating the trough. These are theorizable boundary conditions, not mere caveats; cross-national replication (e.g., against arm's-length market environments) is the decisive test.

Third, limitations of the antifragility measurement instrument. SCA was measured by a self-developed six-item scale whose items mix outcome-oriented and practice/antecedent-oriented content; although both subscales reproduce the nonlinear structure (Section IV(IV)) and the marker/ULMC checks are reassuring, the scale has no independent validation against objective post-disruption performance, and our evidence for 'surpassing the baseline' is perceptual. Moreover, no resilience scale was administered, so the empirical boundary between SCA and resilience remains untested. Future research should jointly administer SCA and established resilience measures, and integrate objective archival data (performance-baseline changes following each disruption) with self-report scales.

Fourth, informant design and statistical power. All data came from one informant per firm, including 17.7% general staff; excluding them attenuates the moderation terms to marginal significance (Section IV(V)). The H7 effect ($p = .050$) was estimated with approximately .50 power; detecting an interaction of this magnitude with 80% power would require approximately $N = 714$. Both features counsel caution and define concrete replication requirements: multi-informant designs, larger samples powered for small interaction effects under range-restricted moderators, and objective or dyadic data for the inter-organizational path.

Fifth, the ceiling effect of the W variable and its difference-score operationalization. The sample mean of W reached 0.82, with approximately 66% of cases above 0.75, and the balanced-dimension formula cannot distinguish high-high from low-low balance [29, 30]. Although combined-dimension controls and multiplicative robustness checks support our interpretation, replication in samples with greater W variance and with alternative operationalizations remains necessary.

Sixth, the model's extensibility remains to be explored. Future research could introduce contextual variables such as supply chain complexity and industry uncertainty, and could also explore extending this study's framework to service supply chains, platform-based ecosystems, and other broader organizational contexts to examine the boundary conditions of theoretical generalizability. Furthermore, manufacturing enterprises' efforts in supply chain antifragility are closely intertwined with the overall conditions of their industry; cross-industry

comparative research can further reveal the boundary effects of industry-specific factors on the DT-collaboration-SCA pathway.

Seventh, the declining arm of the internal inverted-U rests on the upper tail of the M1 distribution (17.1% of firms) and was confirmed by two of three complementary tests (endpoint-slope and spline tests, but not the two-lines test). The order-ceiling region therefore requires confirmation in samples with richer upper-tail representation-ideally including firms deliberately sampled for extreme process optimization. Relatedly, the below-trough arm of the external U-shape is covariate-sensitive in the two-lines specification (significant under covariate-free Robin Hood knot selection but not under full controls at the quadratic turning point) and warrants confirmation in samples with richer lower-tail representation.

Eighth, the response disposition (550 distributed → 350 usable) and the absence of a pilot study for the self-developed scales are documentation gaps we address transparently in this study; future studies should pre-register screening criteria and scale-development procedures.

Ethics Statement

The survey was conducted on a voluntary and anonymous basis for academic research purposes; respondents were informed of the study's purpose and could decline or withdraw at any time. No personally identifiable information was collected, and formal institutional ethics review was not sought for this anonymous, non-interventional survey.

Data Availability

The dataset and analysis code are available from the corresponding author upon reasonable request.

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Appendix A. Measurement Items

All items were rated on five-point Likert scales (1 = strongly disagree, 5 = strongly agree).

Digital Transformation (DT) - time referent: progress over the past three years

DT1. Our firm has widely deployed industrial internet / IoT devices, enabling real-time networked monitoring of production equipment.

DT2. Our firm uses big-data analytics to guide core supply chain decisions such as procurement planning, inventory management, and logistics scheduling.

DT3. Our core business processes - procurement, production, warehousing, and logistics - have achieved end-to-end digital integration with real-time data flows.

DT4. Our firm is actively introducing artificial intelligence (AI) or machine learning for supply chain demand forecasting, risk early warning, or route optimization.

DT5. Digital transformation has been one of our firm's most important strategic priorities over the past three years, with sustained resource investment and strategic commitment from senior management.

Supply Chain Antifragility (SCA) - time referent: actual performance after disruptions over the past three years

SCA1. After each major supply chain disruption over the past three years (e.g., pandemic shocks, raw material shortages, logistics interruptions), our supply chain's overall response and management capability emerged stronger than before the disruption - not merely restored to its original state.

SCA2. Our firm systematically distills lessons from each supply chain crisis or shock and converts them into concrete improvements in management processes, contingency plans, or system capabilities, forming a continuous learning mechanism.

SCA3. Facing external pressures (e.g., policy changes, market volatility, trade friction), our firm is often able to convert them into opportunities to optimize the supply chain structure, expand the partner network, or develop new supply models - rather than merely responding passively.

SCA4. During supply chain disruptions, our firm not only maintained essential operations but also proactively identified and captured market opportunities exposed by competitors' disruption, achieving relative growth amid the crisis.

SCA5. Our supply chain management team has developed a culture of proactive stress testing - regularly simulating extreme scenarios (e.g., tabletop exercises, supply-cutoff tests) to deliberately expose and strengthen weak links in the supply chain.

SCA6. Overall, compared with three years ago, despite a marked increase in environmental uncertainty and disruption frequency, our supply chain's comprehensive capabilities (response speed, cost control, partner network quality) have improved.

Intra-organizational Collaborative Efficiency (M1) - time referent: current operational status

M1_1. Functional departments (procurement, production, logistics, sales) share accurate and complete operational data in real time; no information silos exist.

M1_2. When supply disruptions or unexpected anomalies occur, departments coordinate a rapid and unified response within a short time.

M1_3. Departments' performance goals are highly aligned, with no conflicting departmental interests; everyone works toward common goals.

M1_4. Cross-departmental decision-making processes are clear and efficient, with a well-defined allocation of responsibilities, authority, and benefits, reducing buck-passing and decision delays.

M1_5. Compared with three years ago, the timeliness and accuracy of interdepartmental information transfer and overall collaboration efficiency have improved significantly.

Inter-organizational Collaborative Efficiency (M2) - time referent: current operational status

M2_1. Our firm has established data-sharing mechanisms with major suppliers, exchanging real-time information on inventory levels, order status, and production plans.

M2_2. Our firm maintains high alignment with core suppliers and key customers on sustainability goals, quality standards, and delivery specifications.

M2_3. Our firm has jointly developed detailed emergency response plans with key suppliers, enabling rapid coordinated action in the event of major supply disruptions.

M2_4. Our digital management systems (e.g., ERP, SCM platforms) connect seamlessly with the systems of major suppliers and customers, reducing manual operations and information lags.

M2_5. Over the past three years, deep collaboration with external supply chain partners has significantly improved our supply chain's overall response speed and disruption-handling capability.

Exploitative Innovation (EXP) - time referent: the past three years

EXP1. Our firm has continuously invested resources in optimizing existing production processes, logistics flows, and supply chain management systems, achieving steady efficiency gains.

EXP2. Through systematic technology upgrades and process standardization, our firm has significantly improved the supply stability and delivery reliability of existing product lines.

EXP3. Our firm has devoted substantial resources to deepening and consolidating existing core supply chain competencies (e.g., lean production, cost control, supplier management), building a sustained advantage.

Exploratory Innovation (EXR) - time referent: the past three years

EXR1. Our firm has actively explored entirely new supply chain models or technological paths (e.g., unmanned warehousing, smart logistics, blockchain traceability), accepting short-term uncertainty risks.

EXR2. Our firm is developing or introducing innovative technologies or business models that may disrupt the existing supply chain architecture (e.g., AI-driven autonomous supply chain decision-making).

EXR3. To gain long-term breakthrough supply chain advantages, our firm is willing to accept short-term efficiency losses or additional costs and persists in exploratory innovation investment.

Marker Variable (MK) - workplace environment satisfaction

MK1. The physical environment of our firm's office / production areas (lighting, temperature, noise control) is satisfactory overall.

MK2. The industrial park / business district where our firm is located offers convenient transportation and commuting.

MK3. Our firm's employee care facilities (canteen, flexible benefits, health check-ups) are satisfactory overall.

Appendix B. Supplementary Statistical Tables

Table B1. A-Path Regressions: DT → Mediators (Unstandardized Coefficients)

Term	B	SE	β	t	p	95% CI
DV = M1 (intra-organizational collaborative efficiency)						
DT	0.406	0.045	0.441	9.07	0.000	[0.318, 0.494]
DV = M2 (inter-organizational collaborative efficiency)						
DT	0.459	0.051	0.449	9.06	0.000	[0.359, 0.559]

Note. Both models include $\ln(\text{employees})$, firm age, industry dummies, and ownership dummies. $R^2 = 0.228$ (M1), 0.201 (M2); ΔR^2 for DT = 0.188 / 0.194 (both $p < .001$).

Table B2. Hierarchical Polynomial Regression on SCA (Models 0–3, Focal Terms; Model Numbering Aligned with Table 5)

Term	Model 0 B (SE)	Model 1 B (SE)	Model 2 B (SE)	Model 3 B (SE)	Model 3 β 95% CI (unstd.)
DT	—	0.315 (0.058)	0.195 (0.065)	0.188 (0.061)	0.167 [0.067, 0.309]
M1	—	—	0.461 (0.066)	0.471 (0.062)	0.384 [0.348, 0.593]
M2	—	—	-0.145 (0.058)	-0.128 (0.055)	-0.116 [-0.237, -0.020]
$M1^2$	—	—	—	-0.479 (0.087)	-0.254 [-0.650, -0.308]
$M2^2$	—	—	—	0.306 (0.069)	0.200 [0.171, 0.441]
R^2	0.057	0.133	0.249	0.341	
ΔR^2	—	0.076***	0.116***	0.092***	

Note. SE in parentheses. Model 0 = controls only; Models 1–3 correspond to Table 5 (Model 1: + DT; Model 2: + linear mediator terms; Model 3: + quadratic terms). All models include $\ln(\text{employees})$, firm age, industry dummies, and ownership dummies (dummy coefficients in Table B5). Continuous predictors mean-centered. ΔR^2 F-change tests: Model 1 vs. 0, $F = 29.38$, $p < .001$; Model 2 vs. 1, $F = 26.11$, $p < .001$; Model 3 vs. 2, $F = 23.22$, $p < .001$. *** $p < .001$. Standardized β and 95% CI (unstandardized metric) shown for Model 3.

Table B3. Curvature-Moderation Models H6 and H7 (Unstandardized Coefficients)

Term	H6 B	SE	β	t	p	95% CI	H7 B	SE	β	t	p	95% CI
DT	0.202	0.061	0.179	3.33	0.001	[0.083, 0.322]	0.193	0.061	0.171	3.17	0.002	[0.073, 0.312]
M1	0.474	0.061	0.387	7.73	0.000	[0.353, 0.595]	0.463	0.062	0.378	7.52	0.000	[0.342, 0.585]
$M1^2$	-0.439	0.089	-0.233	-4.96	0.000	[-0.614, -0.265]	-0.488	0.086	-0.258	-5.66	0.000	[-0.657, -0.318]
M2	-0.133	0.054	-0.120	-2.44	0.015	[-0.239, -0.026]	-0.128	0.055	-0.116	-2.35	0.019	[-0.235, -0.021]
$M2^2$	0.296	0.068	0.193	4.35	0.000	[0.162, 0.430]	0.295	0.068	0.192	4.32	0.000	[0.160, 0.429]
W (balance)	-0.910	0.261	-0.201	-3.49	0.001	[-1.422, -0.397]	-0.165	0.262	-0.036	-0.63	0.530	[-0.680, 0.351]
W × M (linear)	-0.224	0.427	-0.024	-0.52	0.601	[-1.064, 0.617]	0.243	0.412	0.026	0.59	0.555	[-0.566, 1.053]
W × M^2 (curvature)	1.759	0.738	0.141	2.38	0.018	[0.307, 3.211]	-1.360	0.692	-0.114	-1.97	0.050	[-2.721, 0.000]
W^2 (Figure 8 model)	0.989	1.274	0.041	0.78	0.438	[-1.517, 3.495]	—	—	—	—	—	—
R^2	0.365						0.361					

Note. Both models include DT, both mediator paths, W, and all controls ($\ln$ employees, firm age, industry and ownership dummies; dummy coefficients available on request). Continuous predictors mean-centered; β via $B \cdot SD(x)/SD(y)$. The W^2 row is estimated in the Figure 8 response-surface model (H6 specification + W^2 : W^2 B = 0.989, $p = 0.438$); it is not part of the reported H6/H7 hypothesis tests. Interaction-block increments over Model 3: H6 $\Delta R^2 = 0.024$, $F(3, 331) = 4.22$, $p = .006$; H7 $\Delta R^2 = 0.020$, $F(3, 331) = 3.42$, $p = .018$.

Table B4. Marker-Adjusted Partial Correlations Among Study Variables (Controlling Marker Variable)

	DT	M1	M2	W	SCA
DT	1				
M1	0.451	1			
M2	0.433	0.262	1		
W	0.038	0.018	0.013	1	
SCA	0.300	0.414	0.042	-0.109	1

Note. Variables residualized on the marker composite (workplace environment satisfaction) before correlation; lower triangle shown. All partial correlations differ from their zero-order counterparts by ≤ 0.005 and retain their sign and significance.

Table B5. Industry and Ownership Dummy Coefficients (Model 3)

Term	B	SE	t	p	95% CI
Industry 2	0.036	0.084	0.43	0.668	[-0.129, 0.202]
Industry 3	0.038	0.089	0.42	0.671	[-0.137, 0.212]
Industry 4	0.021	0.089	0.24	0.809	[-0.153, 0.196]
Industry 5	-0.085	0.088	-0.97	0.335	[-0.257, 0.088]
Industry 6	-0.144	0.094	-1.53	0.126	[-0.329, 0.041]
Ownership 2	-0.029	0.067	-0.43	0.668	[-0.161, 0.104]
Ownership 3	0.082	0.079	1.04	0.301	[-0.074, 0.237]
Ownership 4	0.109	0.120	0.91	0.364	[-0.127, 0.345]

Note. Referent categories: Industry 1 and Ownership 1 (as coded in the dataset). Dummy coefficients are unstandardized. Control variables $\ln(\text{employees})$ and firm age: $B = 0.040$ ($SE = 0.028$, $p = 0.158$) and $B = -0.008$ ($SE = 0.004$, $p = 0.030$), respectively.