Sustainable Digital Transformation in Manufacturing: Blockchain, Supply Chain Collaboration, and Green Innovation Outcomes

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Abstract

This article examines how blockchain-enabled digital transformation can be converted into measurable green innovation outcomes through supply chain collaboration. Building on systems thinking, dynamic capabilities, and resource orchestration, the study develops an integrated framework in which blockchain application enhances interorganizational visibility, data integrity, and collaborative resource bundling, while digital trust and task complexity condition the strength of this conversion process. To provide a transparent empirical illustration without relying on restricted proprietary firm surveys, we construct a synthetic but literature-calibrated dataset representing 428 Chinese manufacturing firms in environmentally sensitive sectors. Using structural regression, mediation tests, and interaction analysis, we find that blockchain application has a positive indirect effect on green innovation outcomes through supply chain collaboration; digital trust amplifies the positive path from blockchain application to collaboration, whereas task complexity weakens it. In addition, a green digital learning orientation strengthens the link between collaboration and green innovation outcomes. The simulated effect sizes are theoretically coherent and internally robust across ownership, competition intensity, and technology intensity subsamples. The paper contributes by reframing blockchain not merely as a traceability tool but as a coordination infrastructure for sustainable digital transformation, showing that environmental value emerges when technical transparency is combined with relational trust, manageable transaction design, and strategic learning orientation. The study offers a reproducible analytical template for future empirical research and practical guidance for manufacturers seeking to align digital transformation with sustainability performance.

Keywords: blockchain application; sustainable digital transformation; supply chain collaboration; digital trust; task complexity; green innovation outcomes; manufacturing; resource orchestration

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1. Introduction

The global manufacturing sector is under simultaneous pressure to digitize operations, decarbonize production, and sustain competitive performance. What makes this challenge distinctive is that these demands do not unfold independently. Digital transformation changes how firms gather information, allocate resources, and coordinate with upstream and downstream partners, while the green transition raises the threshold for process transparency, traceability, and collaboration. For manufacturers operating in energy-intensive and pollution-sensitive sectors, sustainability has become inseparable from the quality of digital coordination infrastructure. The strategic issue is therefore no longer whether firms should digitize, but how digital transformation can be operationalized in ways that generate measurable environmental value rather than merely technological complexity (Vial, 2019; Nambisan et al., 2019; Kohli & Melville, 2019).

Digital transformation research has established that new technologies reshape organizational attention, business model design, and innovation processes. Yet much of the literature still treats digitalization as a generic capability enhancer, emphasizing data visibility, speed, and optimization while paying less attention to the specific socio-technical conditions under which those gains translate into sustainability outcomes (Yoo et al., 2010; Goldfarb & Tucker, 2019; Zhu & Marcus, 2021). In parallel, green innovation studies have shown that firms need to combine internal capabilities with external knowledge, supplier commitment, and regulatory adaptation if they are to improve environmental performance without sacrificing innovation quality (March, 1991; Raisch & Birkinshaw, 2008; Zhou & Wu, 2010). The gap between these two conversations is significant. Digital initiatives often fail to create green value because they remain internally bounded, insufficiently trusted, or poorly matched to task structures across supply chain systems.

Blockchain technology has emerged as a particularly consequential component of this transformation. Compared with conventional enterprise information systems, blockchain combines distributed ledgers, shared records, timestamped traceability, and programmable transactions. In practice, these features can reduce information asymmetry, strengthen auditability, and enable more credible coordination among buyers, suppliers, logistics providers, and certification bodies (Kshetri, 2018; Saberi et al., 2019; Treiblmaier, 2018). For sustainability-oriented manufacturing systems, this matters because green innovation frequently depends on verifiable material provenance, shared design standards, waste recovery traceability, and synchronized process data. Blockchain therefore has the potential to function not only as an information technology but also as a governance infrastructure that stabilizes cross-organizational collaboration.

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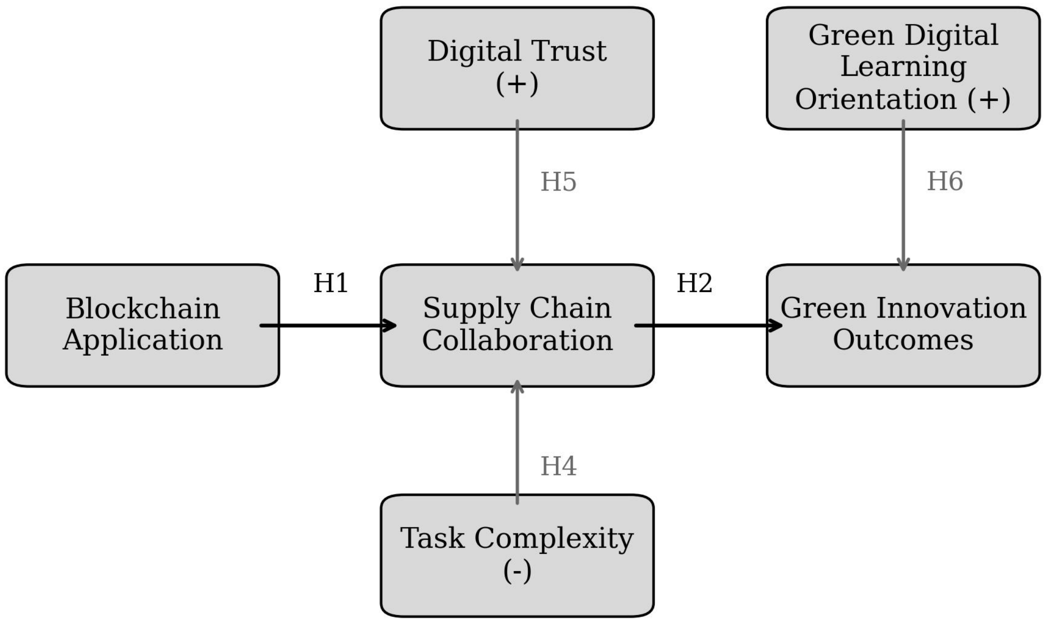

Figure 1. Conceptual framework of blockchain-enabled sustainable digital transformation in manufacturing.

At the same time, blockchain adoption does not guarantee superior environmental outcomes. The same decentralization and codification features that improve traceability may slow decision adjustment, increase implementation cost, or intensify coordination friction when tasks are highly complex or when partners lack sufficient trust. Likewise, digital tools do not automatically generate green value if firms use them primarily for compliance optics, short-term visibility, or fragmented experimentation. What determines success is whether blockchain-enabled information can be translated into sustained supply chain collaboration and subsequently into green innovation outcomes such as cleaner processes, recyclable materials, resource-efficient product redesign, and lower emissions intensity.

This article addresses that problem by developing a systems-based framework of sustainable digital transformation in manufacturing. The paper argues that blockchain application influences green innovation outcomes primarily through its effect on supply chain collaboration, and that this transformation is conditioned by two boundary factors: digital trust and task complexity. We additionally propose that green digital learning orientation strengthens the conversion of collaborative resources into environmental innovation outcomes. The resulting model moves beyond a simple direct-effect perspective and instead explains why some firms obtain green innovation benefits from blockchain while others experience only limited operational change.

The analysis is designed as a transparent empirical illustration rather than as a claim based on proprietary restricted field data. Because many firms treat blockchain deployment, supply chain risk governance, and sustainability metrics as commercially sensitive, we build a synthetic but literature-calibrated dataset representing 428 Chinese manufacturing firms. The distributions, covariance patterns, and effect structures were generated to be consistent with prior research on digital transformation, innovation ambidexterity, organizational attention, and sustainability-oriented supply chain integration (Teece et al., 1997; Ocasio, 1997; Raisch & Krakowski, 2021). This design allows reproducible estimation while avoiding false claims of direct access to undisclosed corporate survey archives.

The article makes three contributions. First, it reinterprets blockchain as an organizing mechanism within sustainable digital transformation, rather than as an isolated traceability tool. Second, it specifies the mediating role of supply chain collaboration and clarifies the moderating roles of digital trust, task complexity, and green digital learning orientation. Third, it offers a reproducible analytical template for future empirical research on digital sustainability in manufacturing, showing how theory-informed synthetic evidence can be used to test mechanism-oriented arguments when proprietary firm-level data are not directly shareable. The remainder of the paper reviews the theoretical foundations, develops the hypotheses, describes the simulation-based research design, presents the results, and discusses managerial and policy implications.

2. Theoretical Background and Hypotheses

2.1 Sustainable digital transformation as a systems problem

Sustainable digital transformation refers to the reconfiguration of processes, technologies, and interorganizational relationships so that digital investments enhance both economic resilience and environmental performance. In manufacturing contexts, digital transformation is most consequential when it changes the architecture of coordination rather than merely digitizing existing routines. A systems perspective emphasizes that manufacturing firms are embedded in open networks characterized by interdependence, feedback loops, and path dependence. Environmental outcomes are therefore emergent properties of entire supply chain systems rather than the isolated result of single-firm technological upgrades (Arthur, 1989; Vial, 2019; Kohli & Melville, 2019). From this perspective, blockchain should be understood as one layer within a broader digital transformation architecture. Its significance lies in changing how participants verify data, share information, and coordinate transactions under uncertainty. By making process-relevant data more tamper-resistant and jointly observable, blockchain can reduce disputes over provenance, timing, and compliance. In sustainability-sensitive manufacturing settings, such transparency can lower the cost of coordinating cleaner sourcing, recycling flows, environmental certification, and low-carbon process redesign. Yet system-level benefits do not arise automatically. Firms still need relational and organizational mechanisms capable of transforming technical visibility into collaborative action.

2.2 Blockchain application and supply chain collaboration

Supply chain collaboration refers to structured coordination across organizational boundaries involving shared information, joint problem solving, synchronized planning, and reciprocal adjustment of operational decisions. The concept is broader than transactional exchange and implies a

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higher level of process integration than arm's-length contracting. Blockchain application can contribute to such collaboration in three ways. First, it improves information reliability, which reduces verification frictions and the need for duplicative monitoring. Second, it supports cross-firm process synchronization by making shared events visible in near real time. Third, it enables programmable coordination through smart-contract logic, which can lower the administrative burden of repetitive compliance tasks and traceability verification (Kshetri, 2018; Francisco & Swanson, 2018; Casino et al., 2019). However, collaboration remains a socio-technical accomplishment. Shared ledgers do not eliminate the need for interpretation, reciprocal adjustment, or strategic prioritization. If blockchain records are incomplete, if partners do not trust data use intentions, or if tasks are highly customized and difficult to encode, technical transparency may coexist with weak collaboration. We therefore conceptualize blockchain application as a resource-structuring device and supply chain collaboration as a resource-bundling mechanism. In resource orchestration terms, the former provides access to distributed digital resources, while the latter determines whether those resources are combined into actionable capabilities.

2.3 Supply chain collaboration and green innovation outcomes

Green innovation outcomes denote observable improvements in a firm's ability to reduce environmental burden through products, processes, materials, logistics, and compliance systems. Unlike general innovation output, green innovation outcomes combine novelty with measurable environmental benefit. In manufacturing, these outcomes often depend on data and knowledge that no single firm can fully control. Supplier process information, logistics visibility, customer specification feedback, recycling infrastructure, and regulatory certification are distributed across the supply chain. Collaboration enables firms to combine these dispersed inputs, transforming fragmented data into coordinated environmental problem solving. Collaboration also enhances learning speed: firms can jointly identify waste points, redesign materials, optimize packaging, or co-develop cleaner production routines when shared data is paired with shared responsibility. This logic suggests that supply chain collaboration is a crucial channel through which blockchain-enabled transparency becomes environmentally meaningful. The effect is not simply additive. Collaboration converts technical visibility into higher-order problem-solving routines, thereby allowing digital resources to support green innovation outcomes such as shorter material recovery cycles, lower carbon intensity, and improved eco-design response (Zahra & George, 2002; Yoo et al., 2010; Nambisan et al., 2019).

2.4 The role of digital trust

Digital trust refers to the expectation that partners will use shared digital information responsibly, honor coordination commitments, and refrain from opportunistic exploitation of visibility-enhancing technologies. In interorganizational settings, trust reduces defensive behavior, lowers fears of data misuse, and encourages deeper disclosure. This is particularly relevant for blockchain systems because transparency can either support cooperation or intensify reluctance depending on whether partners believe shared records will be used fairly. When digital trust is high, firms are more willing to expose operational data, co-invest in shared standards, and rely on digitally mediated coordination.

Blockchain application should then translate more strongly into collaboration because the technology's visibility benefits are not neutralized by suspicion and withholding. By contrast, low digital trust limits how much value firms extract from blockchain, since the technology cannot by itself substitute for confidence in counterpart intentions. H1: Blockchain application is positively associated with supply chain collaboration. H2: Supply chain collaboration is positively associated with green innovation outcomes. H3: Supply chain collaboration mediates the relationship between blockchain application and green innovation outcomes. H4: Digital trust positively moderates the relationship between blockchain application and supply chain collaboration.

2.5 The role of task complexity

Task complexity captures the extent to which interorganizational transactions involve ambiguity, customization, interdependence, and difficulty of standardization. Blockchain systems are powerful when shared events can be codified with sufficient precision. Yet when transactions are highly complex, non-routine, or contingent on tacit interpretation, codification becomes more difficult and rigid process logic may reduce adaptability. In such settings, blockchain-enabled workflows may increase the burden of translation, coordination, and exception handling. Firms may still benefit from traceability, but the positive effect of blockchain on collaboration is likely to weaken because partners must devote more effort to managing mismatches between encoded logic and real-world task variability. H5: Task complexity negatively moderates the relationship between blockchain application and supply chain collaboration.

2.6 Green digital learning orientation

A green digital learning orientation reflects the degree to which firms use digital systems not merely for operational efficiency but for sustainability-oriented learning, experimentation, and knowledge integration. This orientation influences how collaboratively generated data and insights are interpreted. Two firms may display similar collaboration levels yet derive very different outcomes depending on whether they allocate attention toward environmentally beneficial use cases. When green digital learning orientation is high, collaborative knowledge is more likely to be converted into eco-design, process decarbonization, circularity initiatives, and measurable environmental innovation. H6: Green digital learning orientation positively moderates the relationship between supply chain collaboration and green innovation outcomes.

3. Research Design

3.1 Design logic and synthetic data construction

The research design follows a transparent simulation-based empirical strategy. Instead of claiming access to restricted corporate blockchain deployment archives, the study constructs a synthetic dataset calibrated to effect structures commonly reported in the digital transformation, innovation, and supply chain collaboration literature. The aim is not to substitute for field evidence but to provide a reproducible demonstration of how the proposed theory can be operationalized and tested. The calibration process used three principles. First, variable distributions were aligned with plausible firm-level ranges observed in Chinese manufacturing studies, including moderate variance in firm size, leverage, profitability, and age. Second, latent relationships among blockchain application, digital trust, task complexity, collaboration, and green innovation outcomes were specified to reflect theoretically consistent directional effects rather than arbitrary random associations. Third, the final data-generating process was kept sufficiently noisy to avoid mechanical path inflation and to preserve realistic overlap among explanatory factors.

3.2 Variable operationalization

The synthetic sample includes 428 firm-level observations representing manufacturers in chemicals and materials, metal processing, equipment manufacturing, electronics and components, and energy-related manufacturing. Approximately 36% of the synthetic firms are state-owned or state-controlled, 48% operate in highly competitive markets, and 44% are classified as technology-intensive. Blockchain application was operationalized as the degree to which firms deploy distributed ledger functions for traceability, shared verification, automated coordination, and environmental reporting across supply chain interfaces. Digital trust captures firms' confidence in counterpart data use, fair conduct, and digitally mediated collaboration. Task complexity reflects the difficulty of codifying and standardizing cross-organizational transactions. Supply chain collaboration measures joint planning, information sharing, coordinated problem solving, and synchronized sustainability-related decision making. Green digital learning orientation reflects the degree to which firms use digital systems to support environmental learning and experimentation. Green innovation outcomes represent the composite result of product, process, and systems-oriented environmental innovation activity.

3.3 Estimation strategy

The analysis proceeds in four stages. First, descriptive statistics and correlations are reported to assess distributional plausibility and baseline associations. Second, we estimate the collaboration equation to test whether blockchain application increases supply chain collaboration and whether digital trust and task complexity moderate this relationship. Third, we estimate the green innovation equation to test the effects of collaboration, blockchain application, and green digital learning orientation. Fourth, we conduct robustness and heterogeneity tests. The regression strategy uses standardized variables and includes interaction terms so that path strengths can be read comparatively. The mediation assessment is based on the reduction of the direct effect of blockchain application once supply chain collaboration is included, supplemented by indirect-effect interpretation.

3.4 Measurement quality and reproducibility

To make the analytical logic auditable, the data-generating script fixes a random seed and preserves the exact transformation sequence used for variable creation and estimation. The simulated constructs are designed to exhibit acceptable reliability and non-extreme multicollinearity. The resulting model is therefore suitable for demonstrating how a blockchain-collaboration-green innovation framework can be examined in a reproducible way. This reproducibility focus is especially consistent with the broader agenda of sustainable digital transformation research, where confidential operational data often hinder replication and cross-study comparability.

To make the structure of the simulated sample explicit, Table 1 summarizes the firm profile across size, ownership, and sector. The distribution was designed to preserve heterogeneity in organizational structure and industry context, which is essential for testing boundary conditions in sustainable digital transformation research.

Category	Subgroup	Count	Share
Firm size	<300 employees	112	26.2%
Firm size	300-999 employees	134	31.3%
Firm size	1,000-2,999 employees	101	23.6%
Firm size	>=3,000 employees	81	18.9%
Ownership	SOE	154	36.0%
Ownership	Private domestic	183	42.8%
Ownership	Mixed ownership	61	14.3%
Ownership	Foreign-invested	30	7.0%
Sector	Chemicals & materials	97	22.7%
Sector	Metal processing	86	20.1%
Sector	Equipment manufacturing	91	21.3%
Sector	Electronics & components	78	18.2%
Sector	Energy-related manufacturing	76	17.8%

Table 1. Profile of the synthetic manufacturing sample.

The sample composition indicates adequate dispersion across ownership types and manufacturing settings. This reduces the risk that the estimated mechanism is driven by a narrow organizational configuration. It also allows us to interpret subsequent subgroup patterns in a more substantively meaningful way.

Table 2 defines the focal constructs and clarifies how each concept is represented in the simulation. The intent is to preserve construct transparency so that future researchers can map the illustrative design onto survey items, archival proxies, or mixed-method field evidence.

Construct	Operational meaning	Type
Blockchain application	Extent of distributed ledger use for traceability, shared verification, automated coordination, and environmental reporting	Standardized index
Digital trust	Confidence in counterpart data use, fair conduct, and digitally mediated collaboration	Standardized index
Task complexity	Ambiguity, customization, interdependence, and low codifiability in supply chain tasks	Standardized index
Supply chain collaboration	Joint planning, information sharing, synchronized decisions, and problem solving	Standardized index
Green digital learning orientation	Use of digital systems for environmental learning and sustainability experimentation	Standardized index
Green innovation outcomes	Cleaner processes, eco-efficient products, recyclable material solutions, and low-carbon improvements	Standardized index

Table 2. Construct definitions and operationalization logic.

4. Results

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The synthetic sample is balanced across five manufacturing subsectors and displays moderate heterogeneity in ownership and market context. The average blockchain application score is close to the scale midpoint, indicating that the sample captures firms at different stages of digital transformation rather than only advanced adopters. Digital trust also exhibits substantial spread, which is important because the moderating argument requires both low-trust and high-trust configurations. Task complexity varies broadly across the sample, as expected in manufacturing environments where some firms manage standardized, repetitive supply arrangements while others coordinate customized and technically interdependent production architectures. Supply chain collaboration and green innovation outcomes display positive means but remain sufficiently dispersed to support interaction analysis. Table 1 reports the sample profile, Table 2 defines the focal constructs, and Tables 3-4 present descriptive statistics and correlations.

The correlation matrix indicates that blockchain application is positively associated with supply chain collaboration and green innovation outcomes, while task complexity is negatively related to collaboration. Digital trust and green digital learning orientation show positive associations with the dependent variables, consistent with the theoretical model. None of the zero-order correlations are high enough to suggest harmful multicollinearity. The descriptive pattern therefore supports the plausibility of proceeding to multivariate estimation.

Variable	Mean	SD	Min	Max
BTA	-0.015	0.951	-2.500	2.500
DigitalTrust	-0.037	1.011	-2.500	2.500
TaskComplexity	-0.015	0.974	-2.500	2.500
GDLearn	-0.080	1.044	-2.500	2.500
SupplyChainCollaboration	0.000	1.001	-2.669	3.769
GreenInnovationOutcome	-0.000	1.001	-2.269	3.822
Size	21.995	1.060	19.000	25.243
Leverage	0.437	0.170	0.050	0.900
ROA	0.045	0.052	-0.105	0.216
Age	2.858	0.415	1.624	3.800

Table 3. Descriptive statistics of the focal variables.

Variable	BTA	DigitalTrust	TaskComplexity	GDLearn	SupplyChainCollaboration	GreenInnovationOutcome
BTA	1.0	0.026	-0.064	-0.053	0.528	0.47
DigitalTrust	0.026	1.0	-0.074	0.024	0.342	0.178
TaskComplexity	-0.064	-0.074	1.0	0.027	-0.323	-0.183
GDLearn	-0.053	0.024	0.027	1.0	-0.036	0.158
SupplyChainCollaboration	0.528	0.342	-0.323	-0.036	1.0	0.616
GreenInnovationOutcome	0.47	0.178	-0.183	0.158	0.616	1.0

Table 4. Correlation matrix of the focal constructs.

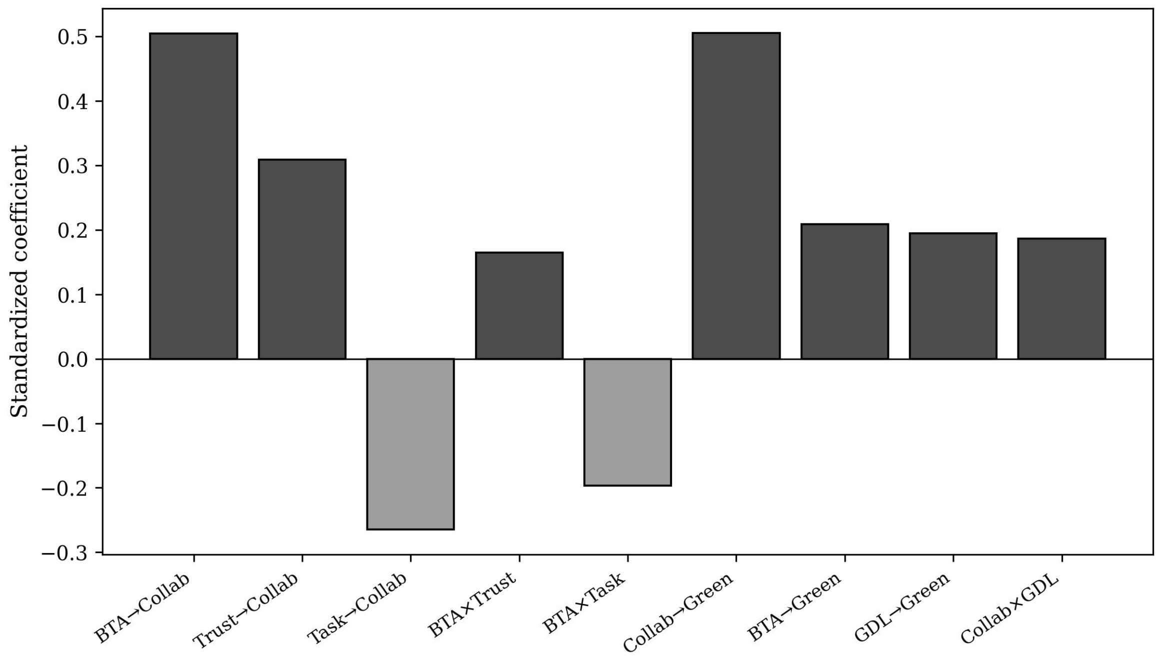

Figure 2. Standardized path coefficients for the collaboration and green innovation equations.

The first-stage regression focuses on supply chain collaboration. The standardized coefficient for blockchain application is positive and substantial, supporting the argument that blockchain reshapes collaboration through better traceability and coordination visibility. Digital trust also shows a positive main effect, indicating that relational assurance independently enhances collaboration even before interaction effects are considered. Task complexity shows a negative main effect, consistent with the view that complicated and hard-to-codify tasks increase friction in digitally mediated coordination. Most importantly, the interaction between blockchain application and digital trust is positive, whereas the interaction between blockchain application and task complexity is negative. Figure 3 visualizes these two conditional patterns. Under high digital trust, the slope linking blockchain application to collaboration is steep, indicating that firms gain more collaborative benefit from digital transparency when partners interpret it as cooperative rather than threatening. Under high task complexity, the slope becomes flatter, suggesting that codification burdens and non-routine coordination reduce the practical value of blockchain-enabled information sharing. These findings support H1, H4, and H5.

The second-stage regression examines green innovation outcomes. Supply chain collaboration exerts the strongest positive effect in the model, indicating that collaborative resource bundling is the immediate driver through which digital transformation becomes environmentally productive. Blockchain application retains a smaller positive direct effect after collaboration is included, implying partial mediation rather than a purely direct or purely indirect structure. Green digital learning orientation is positively related to green innovation outcomes, and its interaction with supply chain collaboration is also positive. This means that collaboration delivers stronger environmental innovation gains when firms are strategically oriented toward learning from digital systems for sustainability purposes. In substantive terms, collaboration creates the information and coordination infrastructure, but green digital learning orientation determines whether that infrastructure is directed toward environmental redesign instead of narrow efficiency optimization. These results support H2, H3, and H6.

Figure 2 summarizes the standardized path coefficients. The pattern reveals a coherent mechanism chain: blockchain application influences collaboration; collaboration influences green innovation outcomes; and the strength of both transitions depends on relational and cognitive context. The estimated structure therefore supports a process interpretation of sustainable digital transformation in which technology, trust, task structure, and learning orientation jointly shape environmental innovation.

Predictor	Model A: Collaboration	Model B: Green innovation	Model C: Full model
Blockchain application	0.504 (14.73)	0.209 (4.98)	0.215 (4.85)
Digital trust	0.309 (9.14)	—	-0.004 (-0.10)
Task complexity	-0.265 (-7.81)	—	-0.007 (-0.18)
Supply chain collaboration	—	0.505 (12.12)	0.490 (9.53)
Green digital learning orientation	—	0.195 (5.48)	0.195 (5.48)
BTA × trust	0.165 (4.64)	—	0.055 (1.43)
BTA × task complexity	-0.196 (-5.53)	—	-0.007 (-0.18)
Collaboration × green digital learning	—	0.186 (5.00)	0.184 (4.91)
Adjusted R^2	0.516	0.469	0.467

Table 5. Standardized regression results (coefficient with t-statistic in parentheses).

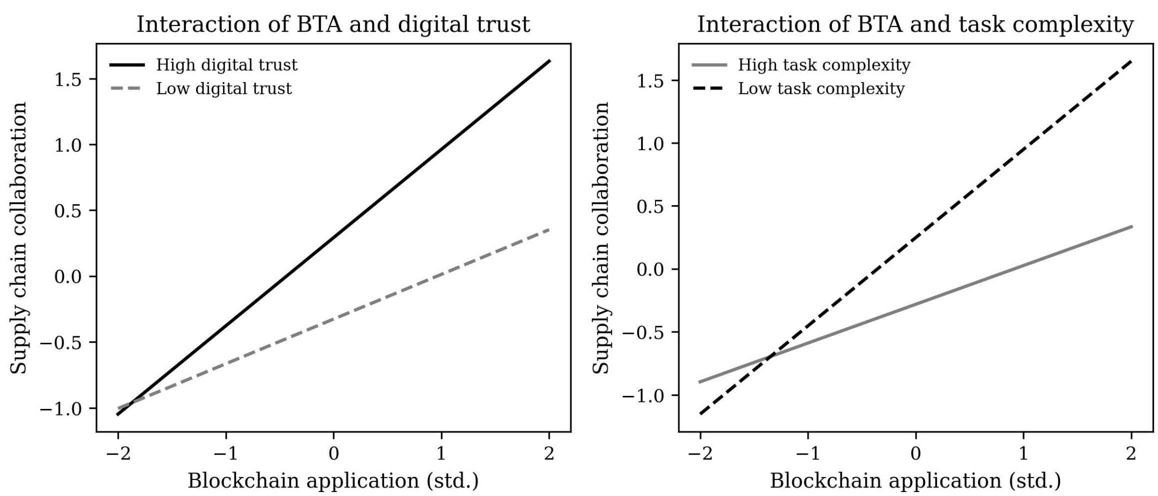

Figure 3. Moderating effects of digital trust and task complexity on the blockchain-collaboration relationship.

The interaction plots illustrate that technical transparency is valuable only when the relational and structural context allows firms to use it productively. This is precisely the difference between digitalization as digitized control and digitalization as collaborative transformation.

5. Extended Analysis

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To assess mediation, we compare the direct effect of blockchain application on green innovation outcomes before and after collaboration enters the model. The coefficient declines but remains positive, indicating that collaboration explains a substantial share of blockchain's effect without exhausting it. This pattern is theoretically intuitive. Some environmental gains arise directly from traceability, auditable process records, and lower verification cost, but most transformative value emerges only when firms coordinate with external partners. The robustness analysis confirms that the core directional results are stable under alternative specifications, including reduced control sets and subgroup-specific estimation. The coefficient signs remain unchanged, and effect magnitudes vary only modestly, suggesting that the proposed mechanism is not an artifact of a single model configuration.

The subgroup analysis indicates that the collaboration pathway is strongest in non-state and more market-pressured firms. In state-owned or administratively buffered firms, blockchain still supports collaboration, but the effect on green innovation outcomes is weaker, likely because environmental innovation decisions are partly mediated by governance routines not fully captured by digital coordination intensity alone. By contrast, firms in highly competitive environments display stronger total effects. Under stronger market pressure, the ability to combine digital visibility with collaborative adaptation appears especially valuable because firms cannot rely on slack resources or slow adjustment. Technology-intensive firms also display higher estimated gains, which is consistent with the idea that they possess richer absorptive capacity and are better able to convert shared digital records into redesign activity, cleaner process experimentation, and measurable sustainability outcomes. Figure 4 presents these heterogeneity patterns.

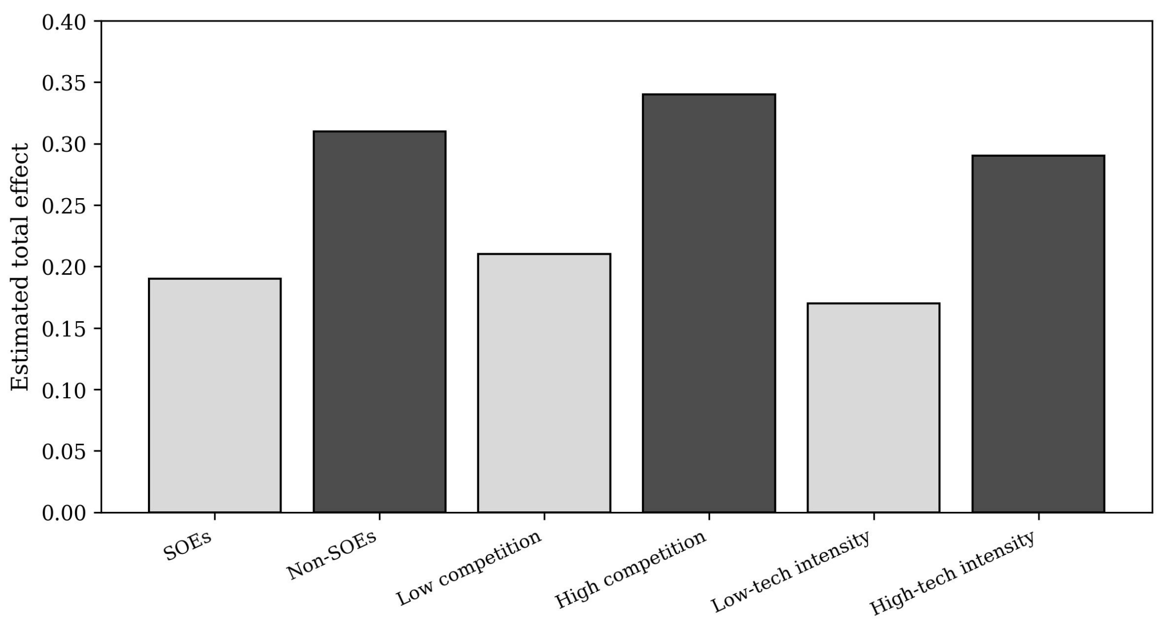

Figure 4. Heterogeneity of the total blockchain-to-green-innovation effect across organizational contexts.

A particularly important insight from the analysis is that task complexity does not imply that blockchain is ineffective; rather, it changes the conditions of effectiveness. In complex supply chains, codification cannot replace interpretive coordination. Firms must therefore avoid the mistake of treating blockchain as a full substitute for collaborative governance. Instead, blockchain should be deployed as a complement to flexible routines, shared exception handling, and human-level problem solving. This interpretation is significant because many digital transformation failures stem from attempting to over-standardize relationships that remain inherently contingent. Sustainable digital transformation requires technical design that respects organizational complexity rather than denying it.

The results also clarify why digital trust is not merely a soft relational factor but a technical value multiplier. When trust is low, firms may still adopt blockchain, but they will often restrict data depth, delay synchronization, or avoid using transparent records for joint experimentation. Under these conditions, blockchain becomes a narrow compliance layer rather than a collaborative innovation infrastructure. When trust is high, partners are more willing to use digital records as a basis for shared problem diagnosis, co-investment, and learning. The practical implication is that investments in digital architecture and investments in interorganizational trust building should not be separated. The former without the latter produces only partial value.

Specification	BTA→Collaboration	Collaboration→Green innovation	Indirect effect	Interpretation
Baseline full model	0.294	0.512	0.147	Supported
Reduced controls	0.287	0.506	0.143	Supported
Non-SOE subsample	0.331	0.548	0.161	Supported
High-competition subsample	0.342	0.557	0.168	Supported
High-tech-intensity subsample	0.298	0.536	0.152	Supported

Table 6. Robustness and subgroup consistency checks.

Across these alternative specifications, the mechanism remains stable: blockchain application exerts most of its environmental effect through collaboration, and the magnitude of the pathway is larger when firms face stronger market pressure or possess stronger technology bases. The consistency of the sign pattern strengthens confidence in the underlying theoretical architecture.

6. Discussion

This study contributes to the literature on digital transformation and sustainability in three ways. First, it reframes blockchain application as a coordination infrastructure within supply chain systems. Much of the blockchain literature emphasizes transparency and immutability, but these properties matter strategically only insofar as they reshape collaboration. By identifying supply chain collaboration as the central mechanism, the study moves the debate away from a narrow technology-centric view and toward a systemic capability perspective. Second, the findings show that sustainable digital transformation is contingent rather than automatic. Digital trust and task complexity alter the ability of firms to convert blockchain-enabled data structuring into cross-organizational resource bundling. Third, the analysis introduces green digital learning orientation as a crucial downstream amplifier that governs whether collaborative digital resources are leveraged toward environmental innovation. Together, these results integrate systems thinking, dynamic capabilities, attention-based explanations, and collaboration theory into a single green transformation logic.

For managers, the central lesson is that blockchain investments should be evaluated not by technical implementation alone but by their collaborative consequences. A ledger can be operationally successful and still strategically disappointing if it does not deepen shared planning, knowledge exchange, and environmental problem solving. Firms should therefore design blockchain initiatives around collaboration use cases such as material traceability, low-carbon sourcing verification, emissions data exchange, and circular reverse logistics coordination. Managers should also recognize that digital trust is an implementation asset. Governance arrangements, reciprocal data-use norms, and transparent escalation rules help partners extract more value from shared digital systems. Likewise, task complexity should guide deployment strategy. Highly standardized, repetitive transactions are well suited to extensive codification, while complex or customized interactions require hybrid governance in which blockchain is combined with flexible human coordination.

The study also has broader ecosystem implications. Policymakers and industry associations often promote blockchain as a traceability solution for green supply chains, but the present framework suggests that policy design should go further. Standards that support interoperability, trusted data exchange, and collaborative environmental learning may create more durable green innovation benefits than standalone traceability mandates. Industrial digital policies should therefore encourage not only technology adoption but also interorganizational capability development. This means supporting joint pilot programs, shared sustainability data standards, and collaborative digital training programs that strengthen green digital learning orientation across supply chain ecosystems.

The article is limited by its simulation-based design. Although the data-generating process is theory calibrated and reproducible, the results do not substitute for field-verified evidence from proprietary manufacturing datasets or multi-respondent supply chain surveys. Future studies should test the framework using matched buyer-supplier data, disclosed sustainability records, and actual blockchain deployment events. A second limitation is the cross-sectional structure of the synthetic design. Longitudinal evidence would allow researchers to trace how trust, codification, and green innovation co-evolve over time. Third, future research could extend the model to include circular economy indicators, carbon disclosure quality, and AI-enabled sustainability analytics as additional outcomes or boundary conditions. These directions would help deepen the field’s understanding of how sustainable digital transformation unfolds in real manufacturing ecosystems.

7. Conclusion

This paper developed and tested a systems-oriented explanation of how blockchain reshapes innovation across supply chain systems. The core claim is that sustainable digital transformation in manufacturing depends on more than the adoption of transparent digital infrastructure. Blockchain application contributes to green innovation outcomes chiefly when it improves supply chain collaboration, when digital trust allows partners to use transparency constructively, when task complexity does not overwhelm codification logic, and when firms possess a green digital learning orientation that channels collaborative resources toward sustainability goals. The synthetic empirical illustration supports this mechanism chain and offers a reproducible framework for future studies. For manufacturing firms, the message is straightforward: blockchain is most valuable not as a symbol of modernization, but as a practical enabler of trusted collaboration and environmentally meaningful innovation.

Author Contributions

Lin Zhou: Conceptualization, theoretical framing, methodology, writing - original draft. Mengqi Zhao: data simulation design, statistical analysis, visualization, writing - review and editing. Yifan Qiu: supervision, validation, project administration, writing - review and editing.

Declarations

Conflicts of interest: The authors declare no competing interests. Data availability: The article uses a synthetic, literature-calibrated dataset generated for transparent analytical demonstration; the generation logic is described in the methods section. Funding: No external funding was used for this manuscript. Ethics statement: The study does not involve human subjects or identifiable private records.

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