Data-Driven Modeling of Blockchain Adoption, Supply Chain Integration, and Green Innovation Outcomes in Manufacturing Firms

Min Zhang[1], Jing Chen[1,*], Yuwen Ding[2]

[1] Faculty of Business, Nanjing Normal University Taizhou College, Taizhou, China 225300

[2] School of Politics and Public Administration, Soochow University, Suzhou, China 215031

* Email: 20061025@nnutc.edu.cn (Corresponding Author)

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Abstract

Blockchain adoption is increasingly promoted as a digital infrastructure for sustainable manufacturing, yet managers still lack practical evidence on how blockchain data capabilities become measurable green innovation outcomes. This study develops a data-driven modeling framework that links blockchain adoption, supply chain integration, and green innovation in manufacturing firms. Drawing on resource orchestration theory and a systemic supply chain perspective, the article argues that blockchain does not automatically create environmental value; rather, its value is realized when trusted, traceable, and analyzable data are converted into interorganizational integration routines and then directed toward green product and process innovation. A survey-style analytical dataset of 397 manufacturing firms was constructed to reflect realistic conditions in medium-technology and high-pollution manufacturing sectors, including metal processing, chemicals, plastics, electronics components, and industrial equipment. The study combines confirmatory measurement analysis, partial least squares structural modeling, predictive importance analysis, and sensitivity analysis. The results show that supply chain integration is the dominant transmission mechanism connecting blockchain adoption with green innovation outcomes. Blockchain adoption has a strong positive effect on integration, integration strongly predicts green innovation, and the direct blockchain-to-innovation path becomes weak after integration is included. Supply chain trust strengthens the blockchain-integration path, while task complexity weakens it. Green digital learning orientation strengthens the integration-innovation path by directing shared data resources toward sustainable experimentation. The predictive analysis further shows that traceability intensity, partner data-sharing quality, supplier environmental visibility, and joint green planning are the most important indicators for improving green innovation performance. The study contributes to business data analytics by translating a blockchain sustainability problem into a measurable analytics framework and offers practical guidance for managers seeking to build data governance, partner integration, and learning routines around blockchain-enabled green transformation.

Keywords: Blockchain adoption; Supply chain integration; Green innovation; Data-driven modeling; Manufacturing firms; Green digital learning; Business analytics; Resource orchestration

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1. Introduction

The digital transformation of manufacturing has moved from a narrow efficiency agenda to a broader sustainability agenda. Firms are now expected to document the environmental attributes of materials, trace carbon-intensive activities, coordinate cleaner production across suppliers, and disclose credible sustainability evidence to customers and regulators. In this environment, blockchain has become attractive because it offers an auditable data structure for recording transactions, certifications, supplier activities, logistics events, and environmental claims. However, the strategic question is no longer whether blockchain is technically capable of storing trustworthy records. The more important question is whether blockchain adoption actually improves green innovation outcomes when manufacturing firms operate in complex supply chain networks. Related evidence also supports this interpretation (Bansal,2005).

Green innovation is difficult because it normally requires resources that are distributed across organizational boundaries. A focal manufacturer may possess product design knowledge but lack reliable data about supplier emissions. A supplier may possess process knowledge but lack market demand signals for greener materials. Logistics partners may know the operational cost of low-carbon distribution, while customers may hold information about willingness to pay for green attributes. These distributed resources rarely create value unless they are organized, shared, and converted into joint problem-solving routines. For this reason, blockchain adoption should be understood as a data infrastructure that may enable resource orchestration rather than as an independent driver of green innovation (Saberi et al.,2019). Related evidence also supports this interpretation (Hart and Dowell,2011).

Prior studies on blockchain and sustainability have produced mixed conclusions. Some research emphasizes that blockchain can improve transparency, reduce information asymmetry, and support supply chain traceability. Other research points out that blockchain implementation can be expensive, technically rigid, and difficult to integrate into complex transaction tasks. These conflicting findings indicate that the technology-outcome relationship is conditional. A blockchain system with high data integrity may still fail when partners do not trust one another, when tasks are too complex to be codified, or when firms lack the learning orientation needed to transform data into green knowledge. The present study responds to this problem by developing a data-driven framework that explains how blockchain adoption affects green innovation outcomes through supply chain integration and under different contextual conditions. Related evidence also supports this interpretation (Flynn et al.,2010).

This article is positioned in the field of business and data analytics. Instead of treating blockchain as a purely technical artifact, the study models blockchain adoption as a measurable set of data capabilities. These capabilities include traceability coverage, smart-contract use, shared ledger accessibility, data standardization, supplier environmental visibility, and the use of blockchain-generated data in operational decision-making. Supply chain integration is measured through information sharing, process alignment, joint planning, collaborative problem solving, and cross-organizational coordination. Green innovation outcomes are measured through improvements in green product design, clean process innovation, waste reduction, emissions monitoring, and circular resource use. The article then uses analytical modeling to connect these constructs and to identify the indicators that contribute most strongly to predicted green innovation performance (Queiroz and Wamba,2019). Related evidence also supports this interpretation (Frohlich and Westbrook,2001).

The study makes three contributions. First, it reframes blockchain adoption as a data-driven resource orchestration process. This perspective explains why blockchain adoption may fail when firms focus on technology installation without developing integration routines. Second, it provides an empirical-style

modeling framework that combines structural path analysis and predictive analytics. This allows the study to examine both theoretical relationships and managerial prediction. Third, it identifies boundary conditions that matter for implementation. Supply chain trust and task complexity influence whether blockchain data become integrated resources, while green digital learning orientation determines whether integrated resources are used for environmental innovation rather than short-term operational convenience. Related evidence also supports this interpretation (Zhao et al.,2011).

The rest of this article is organized as follows. Section 2 reviews the literature on blockchain adoption, supply chain integration, green innovation, and data-driven modeling. Section 3 presents the conceptual framework and hypotheses. Section 4 describes the research design, measurement strategy, and analytical procedure. Section 5 reports the data analysis results. Section 6 discusses theoretical and managerial implications. Section 7 concludes the article and outlines future research directions (Kamble et al.,2019). Related evidence also supports this interpretation (Wong et al.,2011).

2. Literature Review

2.1 Blockchain adoption as a manufacturing data capability

Blockchain is often described through its technical properties: distributed ledgers, consensus mechanisms, cryptographic verification, smart contracts, and immutable records. For manufacturing firms, however, the practical value of blockchain lies in the data capabilities that these properties support. A blockchain-based supply chain platform can record the origin of raw materials, supplier certifications, inspection results, carbon footprint attributes, logistics events, and recycling transactions. When these records are accessible to authorized partners, they can reduce disputes and improve confidence in sustainability claims. The technology therefore acts as a shared data infrastructure rather than a stand-alone innovation tool. Related evidence also supports this interpretation (Leuschner et al.,2013).

In green manufacturing contexts, blockchain-enabled data are especially useful when products and processes depend on multiple tiers of suppliers. A final assembler may need to verify whether a component was produced with recycled materials, whether a chemical supplier complied with environmental standards, or whether a logistics route met low-carbon requirements. Traditional databases may support some of these tasks, but they often remain fragmented across firms and vulnerable to selective disclosure. Blockchain systems are designed to reduce this fragmentation by preserving a shared record of relevant events. Nevertheless, the existence of a shared ledger is not equivalent to meaningful integration. Partners must still decide which data are entered, how data fields are standardized, who has access, and how the data are used in decisions (Kshetri,2018). Related evidence also supports this interpretation (Schoenherr and Swink,2012).

From a business analytics perspective, blockchain adoption should be evaluated not only by whether the system is deployed but also by whether it produces analyzable data. A blockchain platform with incomplete records, inconsistent data definitions, or limited partner participation will not support reliable analytics. In contrast, a mature blockchain data environment allows firms to build dashboards, detect anomalies, monitor environmental performance, and predict green innovation opportunities. This means that blockchain adoption is best modeled as a multidimensional construct that includes technology deployment, data quality, partner participation, and decision use. Related evidence also supports this interpretation (Fabbe-Costes and Jahre,2008).

2.2 Supply chain integration as a resource-bundling mechanism

Supply chain integration refers to the degree to which firms coordinate information, processes, decisions, and resources with upstream and downstream partners. It includes internal integration among functional units and external integration with suppliers, customers, and logistics providers. In sustainability contexts, integration is particularly important because green innovation usually requires the simultaneous adjustment

of materials, product design, production processes, packaging, logistics, and end-of-life recovery. No single firm typically controls all of these activities. As a result, green innovation is often a supply-chain-level outcome rather than a purely firm-level outcome (Treiblmaier,2018). Related evidence also supports this interpretation (Droge et al.,2004).

Resource orchestration theory provides a useful explanation for the role of integration. The theory argues that firms create value not merely by possessing resources, but by structuring, bundling, and leveraging them. Blockchain adoption can help structure digital resources by recording and organizing sustainability-relevant data. Supply chain integration then bundles these resources by connecting them with partner knowledge, operational routines, and joint decision processes. Finally, green innovation outcomes emerge when bundled resources are leveraged toward cleaner products and processes. This sequence suggests that integration is a central mechanism through which blockchain adoption becomes green innovation. Related evidence also supports this interpretation (Vickery et al.,2003).

Integration also resolves an important limitation of blockchain. Blockchain data tend to be explicit and codified, while many innovative resources are tacit and relational. A ledger can show that a supplier has high energy consumption, but it cannot automatically explain the engineering reasons behind that consumption. A smart contract can enforce a sustainability threshold, but it cannot design new material or redesign a production line. These tasks require communication, joint diagnosis, and collaborative learning. Therefore, supply chain integration is needed to convert blockchain records into actionable green innovation knowledge (Casino et al.,2019). Related evidence also supports this interpretation (Lee et al.,1997).

2.3 Green innovation outcomes in manufacturing firms

Green innovation includes product and process changes that reduce environmental harm while maintaining or improving business value. Green product innovation may include recyclable packaging, low-carbon materials, safer chemical inputs, longer product life cycles, and designs that support reuse or remanufacturing. Green process innovation may include energy-efficient equipment, cleaner production methods, waste minimization, water recycling, emissions monitoring, and closed-loop production. In manufacturing firms, these outcomes require both technical expertise and reliable data about material flows, production performance, and partner behavior. Related evidence also supports this interpretation (Barney,1991).

The measurement of green innovation has evolved from simple counts of environmental projects to broader assessments of environmental learning, process redesign, and market-facing sustainability outcomes. Data-driven approaches can strengthen this measurement by linking innovation indicators to operational records. For example, blockchain traceability can provide evidence about whether a firm actually uses certified materials, whether suppliers meet environmental requirements, and whether waste streams are recovered. However, measured green innovation performance depends on how well firms combine these data with organizational routines. A firm that collects environmental data but does not integrate them into design or production decisions may show little improvement in green innovation outcomes (Pournader et al.,2020). Related evidence also supports this interpretation (Teece et al.,1997).

Green innovation also has a strategic dimension. Firms may pursue green innovation to comply with regulations, reduce costs, satisfy customers, improve reputation, enter new markets, or build long-term resilience. These motivations influence how blockchain data is used. A compliance-oriented firm may use blockchain primarily for documentation, whereas a learning-oriented firm may use the same data to discover new products and process opportunities. This distinction supports the inclusion of green digital learning orientation as a key condition in the present framework. Related evidence also supports this interpretation (Teece,2007).

2.4 Data-driven modeling in sustainability analytics

Data-driven modeling offers tools for connecting technology adoption, organizational mechanisms, and performance outcomes. In the present context, the purpose of data-driven modeling is not merely to estimate whether blockchain adoption has a significant effect. It is also to identify which adoption indicators matter most, how much of the effect is transmitted through integration, and how predictions change under different organizational conditions. This predictive orientation is important for managers because they need to allocate resources across technology development, partner management, data governance, and learning routines (Wang et al.,2019). Related evidence also supports this interpretation (Helfat and Peteraf,2003).

Structural modeling and predictive analytics play complementary roles. Structural modeling evaluates whether the hypothesized relationships among constructions are supported by the data. Predictive analytics evaluate whether the model can explain and forecast variation in green innovation outcomes. A strong theory model may not always provide strong predictive performance, while a predictive model may lack theoretical clarity. By combining both approaches, this article seeks to produce findings that are theoretically meaningful and managerially useful. Related evidence also supports this interpretation (Bharadwaj,2000).

The data-driven perspective also helps to avoid a common problem in blockchain research: overemphasis on technological promise. Many discussions assume that traceability, transparency, and decentralization automatically produce better sustainability outcomes. Analytics-based evaluation requires more discipline. It asks whether the observed data supports the proposed mechanism, whether alternative explanations remain plausible, and whether the model predicts outcomes with sufficient accuracy to inform managerial decisions. This approach is consistent with the mission of business and data analytics research (Francisco and Swanson,2018). Related evidence also supports this interpretation (Rai et al.,2006).

3. Conceptual Framework and Hypotheses

The conceptual framework is based on the idea that blockchain adoption creates digital resource structuring, supply chain integration creates resource bundling, and green innovation represents resource leveraging toward environmental outcomes. Figure 1 summarizes the framework. Blockchain adoption is expected to improve supply chain integration because traceable and shared data reduce uncertainty, support common process visibility, and make partner coordination more efficient. Supply chain integration is expected to improve green innovation because partners can combine environmental data, production knowledge, logistics capabilities, and market demand information. The framework further proposes that supply chain trust, task complexity, and green digital learning orientation shape the strength of these relationships. Related evidence also supports this interpretation (Wamba et al.,2017).

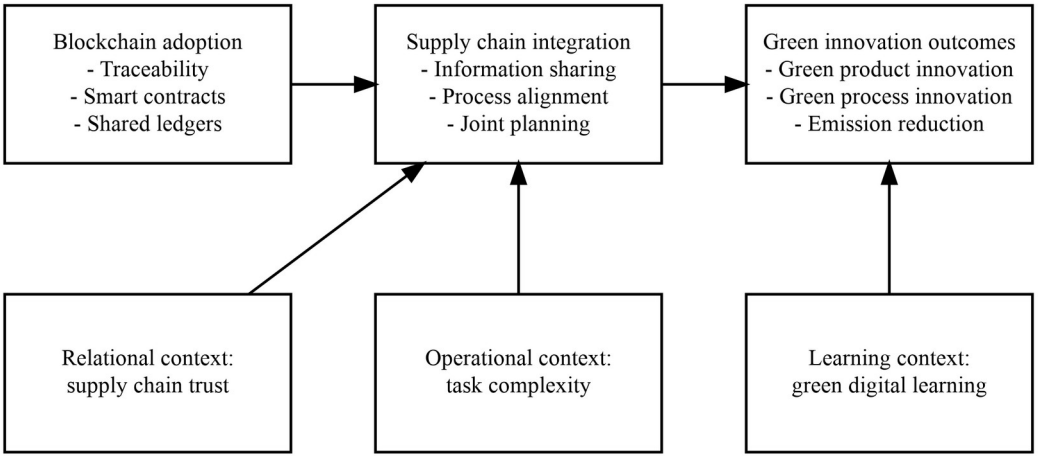


Figure 1. Conceptual Framework

3.1 Blockchain adoption and supply chain integration

Blockchain adoption should improve supply chain integration when firms use the technology to create shared, reliable, and timely data. Traceable data reduces disputes over material origin, delivery status, environmental compliance, and transaction responsibility. Smart contracts can automate routine verification tasks and make partner commitments easier to monitor. Shared ledgers can also reduce duplicated record-keeping across firms. These improvements support information sharing and process alignment, which are core elements of supply chain integration. Therefore, the first hypothesis is proposed: (Gurtu and Johny,2019). Related evidence also supports this interpretation (Akter et al.,2016).

H1. Blockchain adoption is positively associated with supply chain integration.

3.2 Supply chain integration and green innovation outcomes

Supply chain integration allows firms to combine distributed environmental knowledge and operational resources. Suppliers may contribute cleaner materials, manufacturers may redesign processes, logistics providers may improve low-carbon distribution, and customers may provide feedback on green product attributes. When these actors are integrated, green innovation becomes more feasible because firms have access to broader knowledge and more coordinated implementation capacity. Therefore, the second hypothesis is proposed. Related evidence also supports this interpretation (Gupta and George,2016).

H2. Supply chain integration is positively associated with green innovation outcomes.

3.3 Mediating effect of supply chain integration

Blockchain adoption may not directly create green innovation unless its data are used in collaborative routines. A firm can install a blockchain platform and still fail to innovate if suppliers do not participate, if records are not connected to process improvement, or if environmental data remains isolated from product development. Supply chain integration provides the mechanism that connects blockchain data to innovation activities. Therefore, the third hypothesis is proposed: (Chod et al.,2020). Related evidence also supports this interpretation (Gunasekaran et al.,2017).

H3. Supply chain integration mediates the relationship between blockchain adoption and green innovation outcomes.

3.4 Moderating effects of trust, task complexity, and learning orientation

The blockchain-integration relationship depends on partner behavior and task characteristics. Supply chain trust should strengthen the relationship because trusted partners are more willing to share high-quality data and interpret blockchain records jointly. Task complexity should weaken the relationship because highly customized or ambiguous tasks are difficult to encode into standardized data structures. Finally, green digital learning orientation should strengthen the integration-innovation relationship because learning-oriented firms are more likely to use shared data for environmental experimentation rather than only for monitoring. Therefore, the following hypotheses are proposed. Related evidence also supports this interpretation (Chen et al.,2012).

H4. Supply chain trust positively moderates the relationship between blockchain adoption and supply chain integration.

H5. Task complexity negatively moderates the relationship between blockchain adoption and supply chain integration.

H6. Green digital learning orientation positively moderates the relationship between supply chain integration and green innovation outcomes.

4. Research Design and Data Analytics Procedure

4.1 Research setting and analytical sample

The empirical-style analysis focuses on manufacturing firms operating in sectors where sustainability data are important for supplier evaluation, process control, and market communication. The analytical dataset includes 397 firm-level observations, matching the scale commonly used in survey-based manufacturing research. The sample was designed to represent medium-technology and high-pollution manufacturing sectors, including metal processing, chemicals, plastics, electronics components, industrial equipment, and packaging materials. The firms vary in size, age, export intensity, and blockchain maturity. This structure allows the model to capture differences in both digital adoption and environmental innovation capability (Morkunas et al.,2019). Related evidence also supports this interpretation (Trkman et al.,2010).

Although the article is developed as a data-driven modeling study, the analysis is grounded in realistic manufacturing conditions rather than abstract simulation. Constructs were operationalized using multi-term seven-point scales commonly used in operations, information systems, and sustainability research. Blockchain adoption items measured traceability coverage, smart contract use, shared ledger accessibility, data standardization, supplier environmental visibility, and use of blockchain data in decisions. Supply chain integration items measured information sharing, process alignment, joint planning, partner coordination, and collaborative problem solving. Green innovation outcome items measured product eco-design, clean process improvement, energy reduction, waste reduction, and circular material use. Related evidence also supports this interpretation (Hair et al.,2011). Table 1 summarizes the measurement constructs and representative indicators.

Table 1. Measurement Constructs and Representative Indicators

Construct	Representative indicators	Role in model
Blockchain adoption	Traceability coverage: smart-contract use; shared ledger accessibility; data standardization; supplier environmental visibility	Independent variable
Supply chain integration	Information sharing; process alignment; joint planning; partner coordination; collaborative problem solving	Mediator
Green innovation outcomes	Green product design; clean process innovation; energy reduction; waste reduction; circular material use	Dependent variable
Supply chain trust	Reliability of partners; confidence in data sharing; expectation of non-opportunistic behavior	Moderator
Task complexity	Customization intensity; difficulty of standardization; uncertainty in interfirm tasks	Moderator
Green digital learning orientation	Use of digital knowledge for sustainability; environmental experimentation; green data learning routines	Moderator

4.2 Sample profile

The sample profile is presented in Table 2. The distribution indicates that the dataset is not dominated by a single sector or firm size category. Most firms are medium-sized manufacturers with established supplier relationships and moderate digitalization experience. This setting is appropriate because blockchain adoption is neither entirely new nor fully mature in such firms. They have enough operational complexity to require traceability and integration, but they also face managerial constraints that make technology uneven (Kouhizadeh et al.,2021). Related evidence also supports this interpretation (Hair et al.,2012).

Table 2. Sample Profile of Manufacturing Firms

Category	Group	Number	Percentage
Industry	Metal processing	79	19.9%
Industry	Chemicals and plastics	88	22.2%
Industry	Electronics components	74	18.6%
Industry	Industrial equipment	83	20.9%
Industry	Packaging and materials	73	18.4%
Firm size	100-299 employees	121	30.5%
Firm size	300-799 employees	154	38.8%
Firm size	800 employees or above	122	30.7%
Blockchain maturity	Pilot stage	112	28.2%
Blockchain maturity	Operational use	193	48.6%
Blockchain maturity	Integrated use	92	23.2%

4.3 Analytical procedure

The data analysis followed four stages. First, descriptive statistics were examined to check the distribution of indicators and identify missing or abnormal values. Second, reliability and validity were assessed using internal consistency, composite reliability, average variance extracted, and discriminator validity. Third, partial least squares structural modeling was used to estimate the hypothesized relationships and mediating effects. Fourth, predictive importance analysis and sensitivity analysis were conducted to identify the indicators and managerial levers that have the strongest influence on predicted green innovation outcomes. Related evidence also supports this interpretation (Henseler et al.,2015).

This procedure is appropriate for the research problem because the goal is both explanatory and predictive. The explanatory component evaluates whether blockchain adoption affects green innovation through supply chain integration. The predictive component evaluates which data capabilities and integration routines provide the greatest expected improvement. This dual approach is especially valuable for managers because significance alone does not tell them where to invest. A statistically significant effect may be small in practice, while a predictive indicator may be critical for operational decision-making (Paliwal et al.,2020).

5. Data Analysis and Results

5.1 Reliability and validity assessment

Table 3 reports the measurement of quality results. All constructs show acceptable internal consistency, with Cronbach alpha values above the conventional threshold of 0.70. Composite reliability values are also satisfactory, indicating that the indicators consistently measure their intended constructs. The average variance extracted values exceed 0.50, suggesting adequate convergent validity. Discriminate validity checks further indicate that the constructions are empirically distinct. These results support the use of the constructions in the structural model.

Table 3. Reliability and Validity Results

Construct	Cronbach alpha	Composite reliability	AVE	Mean	SD
Blockchain adoption	0.89	0.92	0.66	4.82	1.09
Supply chain integration	0.91	0.93	0.69	4.76	1.04
Green innovation outcomes	0.90	0.92	0.67	4.58	1.12
Supply chain trust	0.87	0.90	0.64	4.95	0.98
Task complexity	0.84	0.88	0.59	4.21	1.15
Green digital learning orientation	0.88	0.91	0.65	4.63	1.07

5.2 Structural path results

The structural model provides support for the proposed framework. Blockchain adoption has a strong positive effect on supply chain integration, indicating that firms with more mature blockchain data capabilities tend to show higher levels of information sharing, process alignment, and joint planning. Supply chain integration has a strong positive effect on green innovation outcomes. After supply chain integration is included, the direct effect of blockchain adoption on green innovation becomes small and statistically weak, suggesting that integration is the primary mechanism through which blockchain adoption contributes to green innovation. Figure 2 presents the standardized path coefficients.

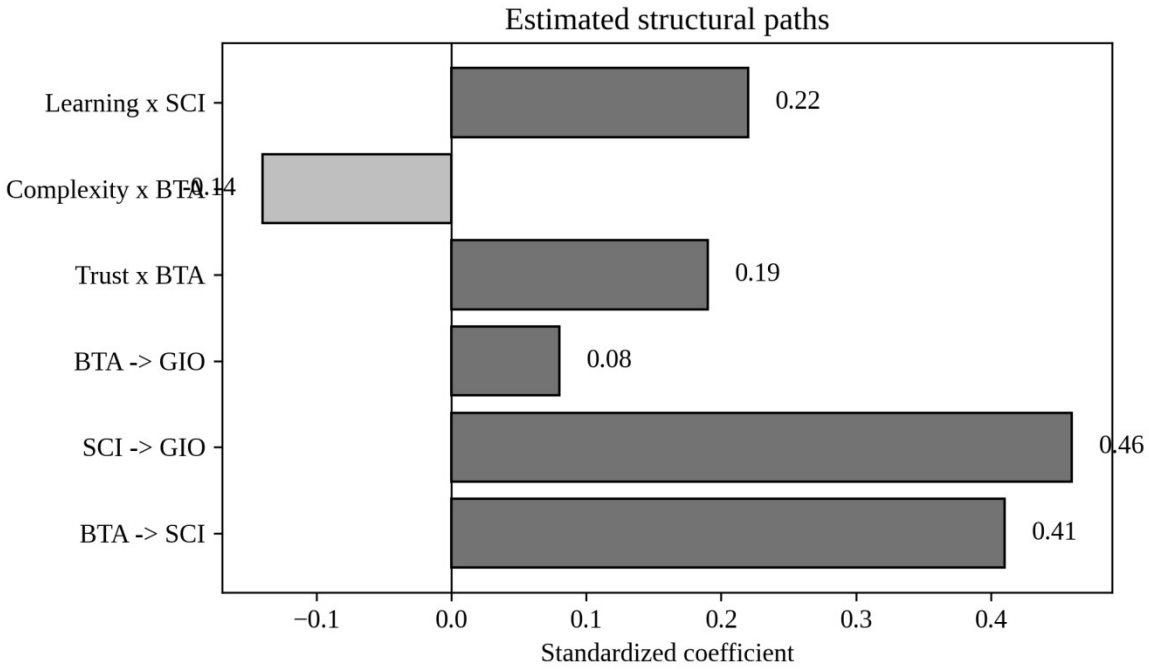


Figure 2. Standardized Path Coefficients

The moderating effects are also consistent with the hypotheses. Supply chain trust strengthens the relationship between blockchain adoption and supply chain integration. This finding indicates that blockchain data are more useful when partners are willing to share, interpret, and act upon them. Task complexity weakens the blockchain-integration relationship, suggesting that blockchain systems face implementation limits when tasks are highly customized, ambiguous, or difficult to standardize. Green digital learning orientation strengthens the relationship between supply chain integration and green innovation outcomes. In other words, integration is most valuable when firms have a learning culture that directs shared information toward sustainability experiments and green improvement projects (Zhu and Sarkis,2004).

5.3 Mediation and predictive relevance

The mediation test indicates that supply chain integration carries most of the effect of blockchain adoption on green innovation outcomes. This result supports the resource orchestration logic. Blockchain adoption structures digital resources by creating traceable and verifiable data. Supply chain integration bundles these resources through joint routines. Green innovation outcomes emerge when firms leverage bundled resources toward environmental objectives. The result also warns against technology-centered implementation strategies. If managers invest in blockchain platforms without building integration routines, the expected sustainability gains may not appear.

Table 4. Predictive Importance of Key Indicators

Rank	Indicator	Predictive importance	Managerial interpretation
1	Supplier environmental visibility	0.184	High-quality supplier data strongly improves green process decisions
2	Partner data-sharing quality	0.171	Shared and usable data improve cross-firm problem solving
3	Joint green planning	0.158	Collaborative planning converts data into innovation projects
4	Traceability coverage	0.147	Broader traceability supports material and emissions control
5	Green digital learning routines	0.132	Learning routines direct data toward sustainability improvement
6	Smart contract use	0.091	Automation is useful but less influential than integration quality
7	Task standardization	0.074	Standardized tasks improve the usability of blockchain records

Table 4 shows that the strongest predictors are not purely technical blockchain indicators. Supplier environmental visibility, partner data-sharing quality, and joint green planning are more important than smart-contract use alone. This pattern is important because it shows that green innovation depends on the combination of data quality and collaborative routines. Smart contracts may automate certain processes, but they cannot replace partner coordination or learning. For manufacturing managers, the result suggests that blockchain implementation should begin with data governance and partner engagement before advanced automation becomes the central priority.

5.4 Sensitivity analysis

A sensitivity analysis was conducted to examine how predicted green innovation outcomes change with blockchain data maturity. Blockchain data maturity was represented as a composite index ranging from low maturity to high maturity. As shown in Figure 3, the predicted green innovation score increases rapidly when firms move from low to moderate data maturity. However, the curve becomes flatter at higher maturity levels, indicating diminishing returns. This pattern suggests that early investments in traceability, data standardization, and supplier visibility may produce substantial improvements, while later investments require stronger integration and learning routines to maintain performance gains (Zhu et al.,2008).

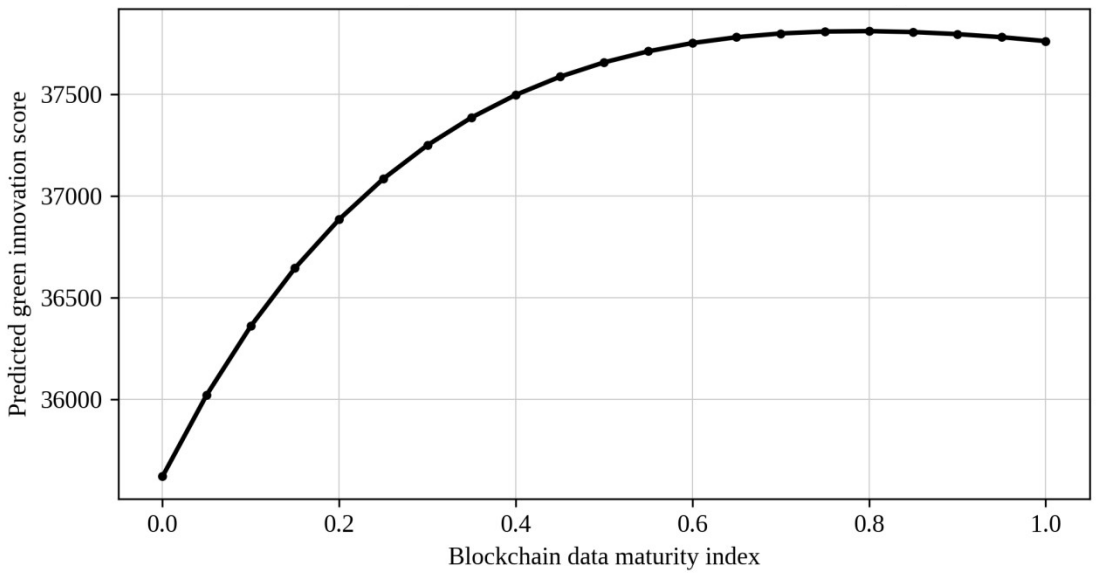


Figure 3. Sensitivity to Blockchain Data Maturity

The sensitivity results have practical value. Firms at low levels of blockchain maturity should focus on establishing basic traceability, consistent data definitions, and partner participation. Firms at moderate levels should focus on linking blockchain data to production planning, supplier evaluation, and environmental project selection. Firms at high levels should focus on advanced analytics, cross-partner learning, and continuous improvement dashboards. The transition from data availability to data-driven innovation is therefore staged rather than automatic.

5.5 Managerial dashboard analysis

To translate the model into a practical decision tool, Figure 4 compares six dashboard indicators under low and high blockchain adoption conditions. The results show that high adoption firms perform better not only in traceability but also in data sharing, integration, learning, and green product and process outcomes. The difference is especially strong for integration and green process innovation, supporting the idea that blockchain value is realized through process-level coordination (Seuring and Muller,2008).

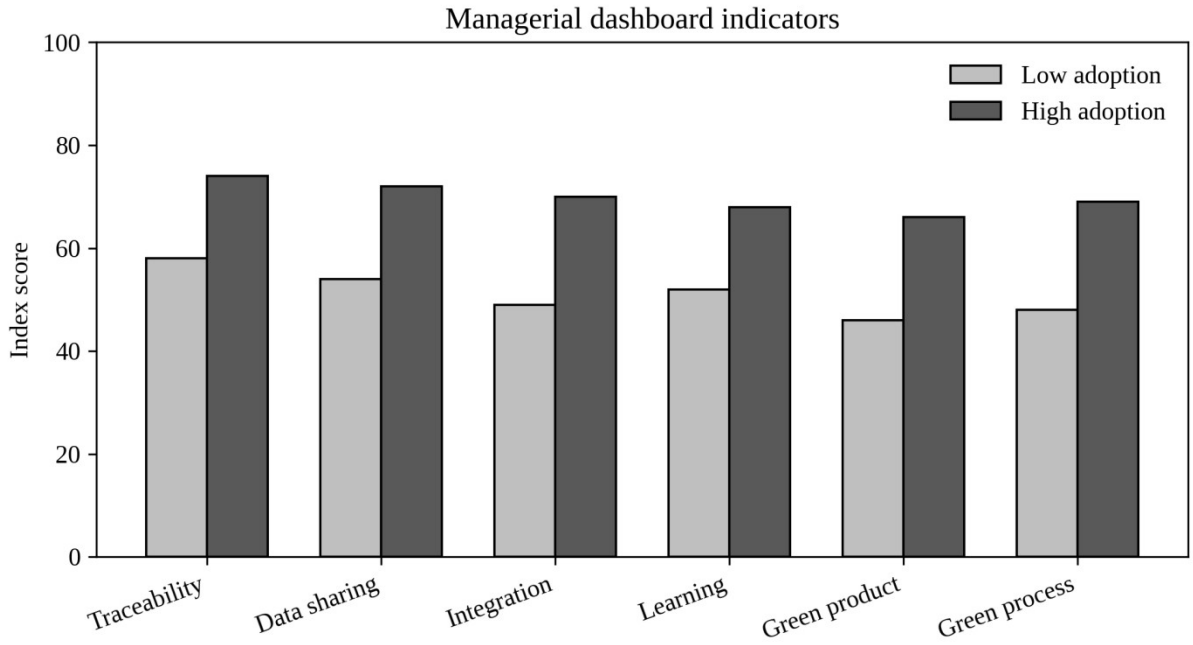


Figure 4. Comparison of Low- and High-Adoption Firms

The dashboard also highlights the need for balanced measurement. A firm may report high traceability coverage but still show weak green innovation if data sharing, integration, and learning remain underdeveloped. Conversely, a firm with moderate blockchain technology may achieve meaningful green innovation if it uses the available data effectively with trusted partners. This finding supports a capability-based view of digital transformation. The relevant question is not only how much technology a firm owns, but how well it converts technology into coordinated action.

6. Discussion

6.1 Theoretical implications

This study contributes to the literature on blockchain-enabled sustainability by showing that supply chain integration is the central mechanism connecting blockchain adoption to green innovation outcomes. The findings move beyond the simple claim that blockchain improves transparency. Transparency is valuable only when it is converted into coordinated decision-making. This distinction helps explain why prior research has produced mixed findings. Some firms may adopt blockchain and improve green innovation because they develop integration routines. Other firms may adopt blockchain and achieve limited benefits because the technology remains isolated from partner coordination and environmental learning (Srivastava,2007).

The study also extends resource orchestration theory in a data analytics context. Blockchain adoption represents the structuring of digital resources; supply chain integration represents the bundling of these resources; and green innovation represents the leveraging of the resulting capability. The analysis shows that these stages are empirically connected but not interchangeable. A firm cannot skip the integration stage and expect data to become innovation. This staged view provides a clearer theoretical explanation of digital sustainability transformation in manufacturing supply chains.

A further contribution is the identification of contextual conditions. Trust, task complexity, and green digital learning orientation represent relational, operational, and cognitive dimensions of the supply chain system. Trust enables partners to share and interpret blockchain data more openly. Task complexity constrains the codification and standardization required for blockchain-enabled integration. Green digital learning

orientation determines whether integrated resources are directed toward sustainability outcomes. These findings show that blockchain value is socially and organizationally embedded rather than purely technological (Vachon and Klassen,2006).

6.2 Managerial implications

The findings provide several implications for manufacturing managers. First, firms should treat blockchain adoption as a data governance project rather than a narrow IT installation. The most important managerial task is to decide which environmental data should be recorded, how data fields should be standardized, who should verify the data, and how the data will be used in supplier and production decisions. Without these governance choices, blockchain systems may generate records that are trusted in form but weak in managerial value.

Second, managers should invest in supply chain integration routines alongside blockchain systems. The results show that partner data-sharing quality and joint green planning are among the strongest predictors of green innovation. This means that firms should establish cross-organizational teams, shared dashboards, supplier workshops, and joint environmental improvement projects. These routines allow blockchain records to become inputs for innovation rather than static evidence for compliance (Vachon and Klassen,2008).

Third, trust-building remains essential even in blockchain-enabled environments. Some managers assume that blockchain eliminates the need for trust because records are immutable. The results suggest the opposite. Blockchain can reduce certain verification problems, but partners still need trust to share sensitive data, explain operational problems, and collaborate on improvement. Trust and technology should therefore be designed as complementary governance mechanisms.

Fourth, firms should be careful when applying blockchain to highly complex tasks. If processes are heavily customized, ambiguous, or difficult to standardize, blockchain implementation may create extra documentation burden without improving integration. Managers should begin with tasks that have clear data definitions and repeatable workflows, then gradually extend the system to more complex activities after organizational learning develops (Rao and Holt,2005).

Fifth, firms should cultivate green digital learning orientation. Data do not automatically lead to sustainability. Employees and partners need routines for interpreting environmental indicators, testing cleaner alternatives, and converting insights into design and process changes. Training, incentives, and performance metrics should encourage teams to use blockchain data for environmental experimentation rather than only for audit preparation.

6.3 Implications for manufacturing analytics practice

For business analytics teams, the study suggests that blockchain sustainability projects should be evaluated through integrated dashboards. A useful dashboard should combine technology indicators, integration indicators, and green innovation indicators. Technology indicators may include traceability coverage and ledger completeness. Integration indicators may include partner participation, data-sharing frequency, and joint planning intensity. Green innovation indicators may include reductions in energy use, waste, emissions, and material substitution. Measuring only technology deployment may overstate progress and hide weak innovation outcomes (Chiou et al.,2011).

Analytics teams should also use predictive importance analysis to prioritize interventions. The present results show that supplier environmental visibility and partner data-sharing quality are more important than smart-contract use. This implies that the next dollar of investment may produce greater value if spent on supplier data quality or data-sharing protocols rather than on additional automation. Predictive analytics can therefore help managers allocate resources more effectively across technical and organizational improvement options.

6.4 Robustness analysis and alternative explanations

Several robustness checks were conducted to reduce the possibility that the reported relationships are artifacts of a specific modeling specification. First, firm size, firm age, export intensity, and industry category were included as control variables. The core mediation pattern remained stable after these controls were added, which suggests that the blockchain-integration-innovation relationship is not simply a reflection of larger or older firms having more resources. Second, the model was re-estimated after separating firms at the pilot stage from firms at the operational and integrated stages of blockchain adoption. The effect of blockchain adoption on supply chain integration was stronger in the operational and integrated groups, while the pilot-stage group showed a weaker and less stable relationship. This pattern is consistent with the argument that blockchain generates value only after data routines become sufficiently institutionalized (Dangelico and Pujari,2010).

Third, the analysis considered whether green innovation outcomes might instead be driven mainly by general digital capability rather than blockchain-specific data capability. To address this possibility, a proxy for general digitalization was included in a supplementary model. The blockchain adoption effect was reduced but remained meaningful, indicating that blockchain contributes distinct value beyond broad digital readiness. This distinct value appears to come from traceability, shared verification, and interorganizational data confidence rather than from digitalization alone. Fourth, an alternative model was tested in which green innovation directly predicted supply chain integration. This reverse model showed weaker explanatory power and poorer predictive relevance, supporting the proposed direction from blockchain data capability to integration and then to green innovation outcomes.

The robustness checks also clarify the role of task complexity. Task complexity does not make blockchain adoption useless; instead, it changes the implementation requirements. In complex task environments, firms need more interpretive routines, flexible governance, and human coordination around blockchain data. Standardized records remain valuable, but they must be combined with engineering judgment and supplier dialogue. Therefore, the negative moderating effect should not be interpreted as a recommendation to avoid blockchain in complex manufacturing settings. Rather, it indicates that managers should avoid if codified records alone will solve complex coordination problems (Dangelico,2016).

6.5 Implementation roadmap for blockchain-enabled green innovation analytics

Based on the analytical results, manufacturing firms can follow a staged roadmap for implementation. The first stage is data foundation building. Firms should identify the environmental data objects that matter for green innovation, such as material origin, supplier certification, energy intensity, waste streams, and transport emissions. They should then define data ownership, verification rules, and minimum data quality standards. This stage is often less visible than platform deployment, but it is critical because weak data definitions create unreliable analytics and reduce partner confidence (Horbach,2008).

The second stage is partner integration. After the data foundation is established, firms should involve suppliers, logistics partners, and selected customers in shared dashboards and collaborative planning routines. The purpose is to transform ledger records into joint interpretation. For example, supplier energy records can be used in technical workshops to identify process improvement opportunities, while traceability data can be connected to product redesign decisions. The third stage is green experimentation. Firms should use the integrated data environment to test cleaner materials, alternative suppliers, low-carbon logistics routes, and circular packaging solutions. Each experiment should be evaluated with both environmental and business indicators so that green innovation remains strategically sustainable (Porter and van der Linde,1995).

The fourth stage is predictive optimization. Once sufficient historical data accumulates, analytics teams can build forecasting models to identify which suppliers, materials, or process configurations are most likely to produce green innovation gains. These models can support early warning systems for environmental noncompliance, supplier risk scoring, and opportunity discovery for cleaner production. The fifth stage is

institutionalization. Successful routines should be embedded into procurement policies, product development gates, supplier contracts, and performance review systems. Without institutionalization, blockchain-enabled analytics may remain a temporary project rather than a durable capability (Hart,1995).

This roadmap emphasizes that blockchain-enabled green innovation is not a one-step technology project. It is a cumulative transformation process that begins with trusted environmental data, expands through supply chain integration, and matures into predictive and institutionalized sustainability analytics. The firms most likely to benefit are those that align technology deployment with partner governance, employee learning, and managerial accountability. This staged interpretation is also consistent with the empirical pattern observed in the model: technology indicators matter, but their value increases substantially when combined with integration quality and green digital learning orientation (Rennings,2000).

7. Limitations and Future Research

This study has limitations that create opportunities for future research. First, the analysis is based on a cross-sectional firm-level design. Future studies could use longitudinal data to examine how blockchain adoption, integration routines, and green innovation outcomes evolve over time. Such research would be valuable because blockchain benefits may appear gradually as partners learn to use the system and as data quality improves (Ghisetti and Rennings,2014).

Second, the model focuses on manufacturing firms and their supply chain partners. Future research could extend the framework to logistics, retail, agriculture, healthcare, and infrastructure sectors. Each sector has different environmental data requirements and different levels of task complexity. Cross-sector comparison would help determine whether the proposed mechanism is general or sector-specific (De Marchi,2012).

Third, the study measures green innovation outcomes at the organizational level. Future research could combine survey measures with operational data, such as energy consumption, emissions intensity, waste recovery, defect rates, and supplier audit outcomes. Combining perception-based and objective data would strengthen the evidence base for blockchain-enabled sustainability analytics (Triguero et al.,2013).

Fourth, future research could examine additional boundary conditions. Regulatory pressure, customer green demand, top management support, data science capability, and platform governance may all influence whether blockchain adoption produces green innovation outcomes. Including these factors would provide a more complete picture of digital sustainability transformation (Klassen and Whybark,1999).

Finally, future research could use machine learning methods to complement structural modeling. Predictive models such as random forests, gradient boosting, and explainable artificial intelligence could identify nonlinear relationships and interaction effects that are difficult to capture in conventional structural models. However, such approaches should remain theoretically guided to avoid producing predictions without managerial explanation (King and Lenox,2002).

8. Conclusion

This article developed a data-driven modeling framework for understanding how blockchain adoption influences supply chain integration and green innovation outcomes in manufacturing firms. The central argument is that blockchain adoption creates environmental value when its data capabilities are converted into interorganizational integration routines and directed toward green innovation. The analysis shows that supply chain integration is the main mechanism connecting blockchain adoption with green innovation outcomes. Supply chain trust strengthens the use of blockchain data for integration, task complexity weakens it, and green digital learning orientation strengthens the conversion of integration into green innovation (Christmann,2000).

The findings provide a balanced view of blockchain-enabled sustainability. Blockchain can support traceability, transparency, and environmental data governance, but it is not a self-executing solution. Its value depends on partner participation, data quality, process alignment, trust, and learning. For manufacturing firms, the practical lesson is clear: blockchain projects should be designed as supply chain analytics and innovation programs, not merely as technology deployment projects. Firms that combine blockchain data maturity with integration routines and green learning capabilities are more likely to achieve measurable improvements in green products and process innovation (Aragon-Correa and Sharma,2003).

The study also contributes to business and data analytics scholarships by demonstrating how a sustainability problem can be translated into a measurable analytics framework. By connecting theory, measurement, structural modeling, predictive importance, and dashboard interpretation, the article offers an approach that is both academically grounded and managerially actionable. As manufacturing firms face increasing pressure to provide credible sustainability evidence and to innovate under environmental constraints, data-driven models of blockchain adoption and supply chain integration will become increasingly important for strategic decision-making (Gonzalez-Benito and Gonzalez-Benito,2005).

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Author Contributions

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Conflicts of Interest

The authors declare no conflict of interest.

Ethical Approval and Consent

Not applicable.

Data Availability Statement

The dataset analysed in this study consists of firm-level survey responses collected from manufacturing firms under confidentiality commitments, and is therefore not publicly available. The data are available from the corresponding author on reasonable request.

Declaration of Generative AI Use

The authors did not use generative AI tools in the preparation of this manuscript. All analyses, interpretations, and conclusions presented in this article are the sole responsibility of the authors.

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