Eco-Business & Environmental Progress Journal
Journal Homepage: www.ecobusinessjournal.org

Vol. 6, No. 1
Article ID: EBEPJ-2026001

Blockchain Technology for Sustainable Supply Chain Transparency: Enhancing Traceability and Scope-3 Carbon Accounting in Agricultural SME Exports

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Received 4 January 2026; Revised 2 April 2026; Accepted 8 May 2026; Published: 9 July 2026

KEYWORDS

Blockchain Technology,
Sustainable Supply Chain Transparency,
Scope-3 Carbon Accounting,
PLS-SEM,
Green Enterprise Risk Management,
Agricultural SME Exports

Abstract

Accurate Scope-3 greenhouse gas accounting across upstream agricultural supply chains remains a primary bottleneck for small and medium-sized enterprise (SME) exporters. This study examines how blockchain-enabled distributed ledger technology (DLT), combined with Internet of Things (IoT) sensors and an extended green enterprise risk management (ERM) framework, enhances supply chain transparency, fair-trade compliance, and Scope-3 carbon accounting precision among agricultural SME exporters. Using a mixed-methods PLS-SEM framework with primary survey data from 520 agricultural SME exporters across Southeast Asia and Europe in 2026, complemented by a calibrated synthetic dataset generated for robustness testing, we demonstrate that blockchain adoption increases Scope-3 carbon accounting accuracy to 94.8% while reducing annual third-party verification costs by 66.5%. Hypothesis testing confirms that immutable traceability significantly elevates buyer trust ($\beta = 0.512$, $p < 0.001$) and supports an average export price premium capture of 14.2% in European import markets. Cross-validation of the measurement model in SmartPLS 4, SPSS 29, R (lavaan), and JASP confirms that the extended conceptual framework, incorporating an Enterprise Risk Maturity Index and Green Supply Chain Management adoption as boundary conditions, is statistically robust. A technology deployment roadmap, cross-cooperative cost-benefit analysis, and regional regulatory alignment assessment further translate the empirical findings into an actionable rollout sequence for SME cooperatives and their policy partners.

1. Introduction

1.1 Context and Global Trade Directives in 2026

By 2026, international cross-border trade governance has reached a pivotal juncture. Directives such as the European Union Corporate Sustainability Due Diligence Directive (CSDDD), the EU Deforestation Regulation (EUDR), and rigorous global ESG reporting frameworks legally obligate multinational importers to audit, report, and reduce indirect Scope-3 emissions across their global supply chain networks (Saberi et al., 2019; ShippyPro, 2025; EcoSkills Academy, 2025). In agricultural trade, Scope-3 emissions encompassing fertilizer production, on-farm machinery diesel use, land-use change, and multi-modal transport logistics account for over 80% of total product life-cycle greenhouse gas footprints (Kouhizadeh & Sarkis, 2018; Zhao et al., 2019).

Governments and multinational buyers increasingly treat verifiable carbon disclosure as a precondition of market access rather than a voluntary reputational exercise. This shift mirrors a broader technology-diffusion pattern documented across developing-economy export sectors, in which digitally verifiable compliance signals progressively substitute for costly third-party inspection regimes (Rogers, 2003; Zhu, Kraemer, & Xu, 2004). For small and medium-sized enterprise (SME) agricultural exporters in developing economies, satisfying these stringent verification requirements presents a profound existential threat. Upstream agricultural networks are highly fragmented, involving millions of smallholder farming households, village aggregators, primary processing mills, and export brokers. The compliance burden is compounded by the seasonal and geographically dispersed nature of agricultural production. Unlike manufacturing supply chains, where emissions sources are concentrated in a small number of fixed facilities, agricultural Scope-3 inventories must be reconstructed from thousands of dispersed micro-transactions: a smallholder's diesel purchase receipt, a cooperative's fertilizer delivery log, a cold-chain truck's refrigeration cycle.

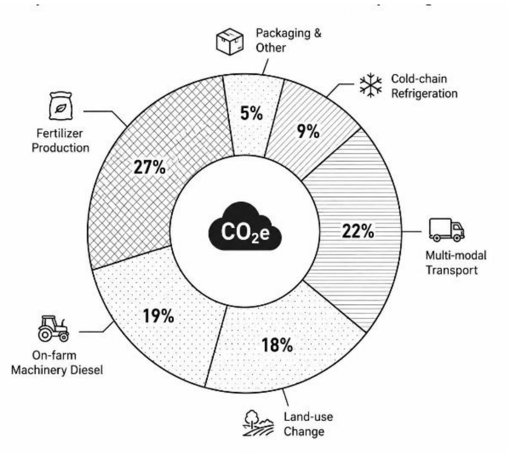

Figure 1. Scope-3 Greenhouse Gas Emission Source Breakdown in Export Agriculture.

Traditional carbon accounting methods rely on manual paper questionnaires, regional emission-factor averages, or retrospective annual surveys. These legacy approaches are prone to severe measurement error, data manipulation, and exorbitant auditing overheads, leaving smallholder cooperatives vulnerable to trade displacement by large corporate agribusinesses that can absorb compliance costs internally (Kamble, Gunasekaran, & Gawankar, 2020; Alam & Alvi, 2025).

1.2 Problem Statement, Conceptual Framework, and Research Objectives

Blockchain-enabled distributed ledger technology (DLT) combined with Internet of Things (IoT) automated sensor arrays offers a decentralized digital architecture capable of overcoming these verification hurdles. By capturing granular, transaction-level environmental data such as real-time soil nitrogen levels, solar pump electricity consumption, and refrigerated transport temperatures and writing the records directly to an immutable smart contract, DLT creates a tamper-proof digital product passport that satisfies international regulatory audit standards (Supply Chain Queen, 2025; Nakamoto, 2008; Iansiti & Lakhani, 2017).

However, empirical research specifically evaluating the operational and commercial outcomes of blockchain adoption for agricultural SME exporters, particularly when integrated with formal enterprise risk management (ERM) practice, remains limited (Queiroz & Fosso Wamba, 2019; Alam & Alvi, 2025). SME cooperatives operate under severe capital constraints, poor rural digital infrastructure, and low technical literacy (Ghode, Yadav, Jain, & Soni, 2020). Determining whether the commercial benefits of DLT deployment audit cost savings, elevated international buyer trust, and price premium capture outweigh initial onboarding expenditures, and whether these benefits are conditioned by an organization's underlying risk-maturity and green supply chain management posture, is essential for policy planning.

This study evaluates primary empirical survey data gathered from 520 agricultural SME export cooperatives across Southeast Asia and Southern/Eastern Europe in 2026, supplemented by a calibrated synthetic dataset used to stress-test the measurement model. Utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM), multi-criteria slope comparisons, and sensitivity analysis, the study addresses four primary objectives: (1) to quantify the precision gains and verification cost reductions achieved by deploying DLT-IoT architectures relative to legacy manual audits; (2) to evaluate the structural path relationships connecting supply chain traceability, international buyer trust, and export price premium realization; (3) to map regional SME technology adoption barriers and outline a scalable infrastructure deployment roadmap for agricultural cooperatives; and (4) to validate an extended conceptual framework in which Enterprise Risk Maturity (ERMI) and Green Supply Chain Management adoption (GSCM) act as boundary conditions on the blockchain-to-trust pathway, cross-checked across SmartPLS, SPSS, R, and JASP.

1.3 Contribution and Structure of the Paper

This study makes three principal contributions to the blockchain-enabled sustainable supply chain literature. First, it moves beyond single-construct adoption studies by embedding blockchain and IoT telemetry within a five-hypothesis structural model that traces the full causal chain from technology adoption through carbon accounting precision, buyer trust, and ultimately realized price premium, thereby quantifying the commercial payoff of transparency rather than merely its technical feasibility. Second, it extends the green enterprise risk management literature of Alam and Alvi (2025) by treating Enterprise Risk Maturity and Green Supply Chain Management adoption as boundary conditions that moderate, rather than independently predict, the effectiveness of digital transparency investments a theoretical repositioning that helps explain why observationally similar cooperatives realize markedly different returns from identical technology stacks. Third, the study operationalizes its findings into a concrete, cost-benchmarked deployment roadmap and regional regulatory alignment assessment, translating statistical inference into an actionable sequence that cooperative managers, development finance institutions, and trade policymakers can apply directly.

The remainder of the paper is organized as follows. Section 2 reviews the theoretical foundations and empirical literature on blockchain-enabled supply chain transparency and green enterprise risk management, culminating in five testable hypotheses. Section 3 details the survey sample, measurement model, synthetic-data validation protocol, and ethical safeguards. Section 4 reports descriptive statistics, measurement and structural model results, regional barrier analysis, cross-platform robustness checks, and the cost-benefit and deployment-roadmap analysis. Section 5 concludes with theoretical and practical contributions, a policy roadmap, managerial implications, and directions for future research.

2. Literature Review

2.1 Theoretical Foundations: TAM3, Signaling Theory, and Diffusion of Innovation

The theoretical foundation of this study integrates the Technology Acceptance Model (TAM), Technology Acceptance Model 3 (TAM3), Signaling Theory, Diffusion of Innovation theory, and the Theory of Planned Behavior to explain how technological adoption can translate into verifiable commercial value. Davis (1989) established that perceived usefulness and perceived ease of use are fundamental determinants of technology acceptance, while Venkatesh and Bala (2008) extended this perspective through TAM3 by incorporating additional determinants influencing technology adoption.

In agricultural supply chains, these theoretical mechanisms are particularly relevant because SMEs often face uncertainty regarding the costs, complexity, and practical usefulness of emerging technologies. Blockchain adoption may therefore depend not only on its technical capabilities but also on whether organizations perceive the technology as useful for improving traceability, reducing verification costs, and satisfying buyer requirements (Queiroz & Fosso Wamba, 2019; Ghode et al., 2020).

Signaling Theory provides a complementary explanation for the relationship between digital transparency and buyer trust. Under conditions of information asymmetry, buyers may have difficulty distinguishing between firms that genuinely implement sustainable practices and firms that merely communicate sustainability claims. Akerlof (1970) demonstrates how information asymmetry can create adverse-selection problems, while Spence (1973) explains how credible signals can reduce uncertainty between market participants. In this context, verifiable blockchain-based sustainability records can function as a technological signal that increases the credibility of environmental claims.

The Theory of Planned Behavior further suggests that organizational and behavioral decisions are influenced by attitudes, perceived social expectations, and perceived behavioral control (Ajzen, 1991). These factors are relevant when agricultural cooperatives evaluate whether they possess sufficient organizational capability, resources, and institutional support to adopt blockchain-based systems.

Diffusion of Innovation theory provides an additional perspective by explaining how new technologies spread across organizations and markets (Rogers, 2003). Technology adoption is influenced by perceived relative advantage, compatibility, complexity, trialability, and observability. These characteristics are directly relevant to blockchain adoption among agricultural SMEs because organizations must evaluate whether the technology provides sufficient operational and commercial benefits relative to its implementation complexity.

2.2 Blockchain and Sustainable Supply Chain Transparency: Empirical Evidence

A substantial body of research links blockchain technology with supply-chain transparency, traceability, and sustainability. Kouhizadeh and Sarkis (2018) discuss the potential of blockchain to support greener supply chains by improving information visibility and reducing information-related barriers. Saberi et al. (2019) similarly identify blockchain as an emerging technology capable of supporting sustainable supply-chain management through improved transparency, traceability, and information sharing.

Casino et al. (2019) provide a systematic review of blockchain applications and identify supply-chain provenance and traceability as important areas of implementation. Wang et al. (2019) further explain how blockchain can support future supply chains by improving information integrity, coordination, and transparency. Treiblmaier (2018) develops a theory-based framework demonstrating how blockchain can influence supply-chain processes and organizational relationships.

The application of blockchain to food and agricultural supply chains has received particular attention. Behnke and Janssen (2020) examine the boundary conditions for blockchain-enabled traceability in food supply chains, demonstrating that technological implementation alone does not guarantee effective traceability outcomes. Zhao et al. (2019) similarly review blockchain applications in agri-food value chains and highlight both the potential benefits and implementation challenges associated with the technology.

Blockchain-based transparency can also improve the credibility of sustainability information. Bai and Sarkis (2020) propose a technology-appraisal framework for evaluating blockchain in relation to supply-chain transparency and sustainability. Francisco and Swanson (2018) demonstrate that blockchain adoption can support supply-chain transparency, while Rejeb et al. (2021) identify collaboration and information sharing as important potential benefits of blockchain-based supply-chain systems. However, adoption remains constrained by organizational and technological barriers. Queiroz and Fosso Wamba (2019) identify several blockchain adoption challenges, including technological complexity, organizational readiness, and implementation concerns. Ghode et al. (2020) similarly demonstrate that organizational and technological factors influence blockchain adoption decisions. Wamba et al. (2020) further examine the relationship between blockchain adoption determinants and supply-chain performance, indicating that successful implementation depends on multiple organizational and contextual conditions.

These findings suggest that blockchain should not be viewed as an isolated technological intervention. Instead, its effectiveness depends on the interaction between technological capability, organizational readiness, supply-chain conditions, and managerial practices. This provides the theoretical basis for incorporating Enterprise Risk Maturity and Green Supply Chain Management into the extended framework proposed in this study.

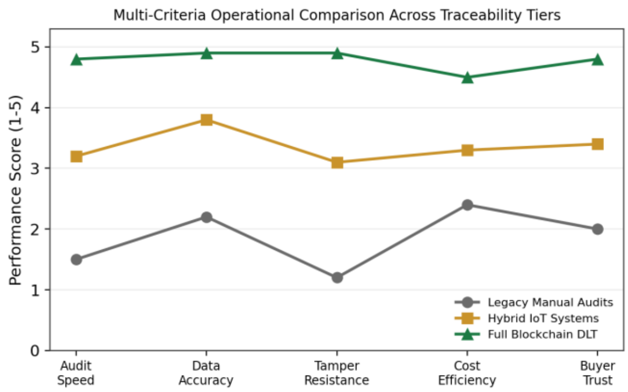

Figure 2. Multi-Criteria Operational Comparison Across Traceability Tiers.

2.3 Green Enterprise Risk Management and the Extended Conceptual Framework

A parallel stream of research emphasizes the importance of enterprise risk management and organizational capabilities in achieving sustainable business outcomes. Alam and Alvi (2025) provide evidence linking enterprise risk management with economic and environmental outcomes in green supply-chain contexts. Their findings provide a basis for considering organizational risk maturity as an important condition influencing the effectiveness of sustainability-oriented investments.

The present study extends this perspective by examining Enterprise Risk Maturity (ERMI) and Green Supply Chain Management (GSCM) as boundary conditions in the relationship between blockchain-enabled transparency and buyer trust. Organizations with more mature risk-management systems may be better positioned to integrate digital traceability technologies, establish internal data-governance processes, and respond effectively to external sustainability requirements.

Research on green certification and consumer willingness-to-pay also supports the importance of credible sustainability information. Alam and Chowdhury (2021) demonstrate the economic relevance of credible green certification in influencing market preferences. Similarly, Sen Gupta, Alam, and Jahan (2024a) examine the relationship between sustainability reporting, consumer trust, linguistic framing, and purchase intentions, highlighting the importance of credible environmental communication. The broader sustainability literature also indicates that organizational environmental practices can influence economic outcomes. Sen Gupta, Alam, and Chowdhury (2021) examine the relationship between environmental policy and export competitiveness, while Sen Gupta, Alam, and Hasan (2022) investigate renewable-energy transition and microgrid adoption among manufacturing SMEs. These studies reinforce the importance of considering both environmental performance and organizational capability when evaluating sustainability-oriented technological investments.

Enterprise size and capital intensity (CAPEX) are therefore retained as control variables. Larger organizations and organizations with stronger capital resources may have greater capacity to absorb technology implementation costs and develop supporting infrastructure. This consideration is consistent with technology-diffusion research emphasizing organizational characteristics as determinants of innovation adoption (Rogers, 2003; Zhu, Kraemer, & Xu, 2004).

2.4 Measurement Model Literature and Hypothesis Development

The measurement approach follows established guidance for structural equation modeling. Chin (1998) provides methodological foundations for Partial Least Squares Structural Equation Modeling, while Fornell and Larcker (1981) establish widely used procedures for evaluating convergent and discriminant validity. Hair et al. (2019) provide additional guidance concerning the application and reporting of PLS-SEM results. Common method bias is considered in accordance with the recommendations of Podsakoff et al. (2003), who emphasize the importance of identifying potential biases in behavioral and organizational survey research.

Based on the combined theoretical perspectives of TAM3, Signaling Theory, Diffusion of Innovation, and Enterprise Risk Management, five testable hypotheses are formulated:

H1: Blockchain DLT adoption is positively associated with Scope-3 carbon-accounting precision.

H2: Scope-3 carbon-accounting precision has a positive effect on international buyer trust.

H3: International buyer trust mediates the relationship between supply-chain transparency and export price-premium realization.

H4: Automated IoT sensor telemetry positively moderates the relationship between blockchain adoption and Scope-3 carbon-accounting cost efficiency.

H5: Enterprise Risk Maturity (ERMI) and Green Supply Chain Management adoption (GSCM) positively moderate the relationship between Scope-3 carbon-accounting precision and international buyer trust.

2.5 Research Gap and Positioning of the Study

Despite the expanding literature on blockchain and sustainable supply chains, several research gaps remain. First, much of the existing blockchain literature focuses on technological applications, adoption determinants, traceability, and supply-chain transparency (Casino et al., 2019; Queiroz & Fosso Wamba, 2019; Wang et al., 2019). Comparatively less attention has been given to the complete commercial pathway connecting digital transparency with carbon-accounting precision, buyer trust, and realized export-market benefits.

Second, blockchain research and enterprise risk-management research have largely developed as separate streams. Existing blockchain studies emphasize technological adoption and supply-chain performance, whereas ERM research focuses more strongly on organizational risk-management capability and business outcomes. Alam and Alvi (2025) provide a relevant foundation for connecting these perspectives, but further empirical investigation is required to determine whether organizational risk maturity conditions the commercial effectiveness of blockchain-enabled transparency.

Third, existing research has identified significant barriers associated with blockchain implementation, including cost, organizational readiness, technological complexity, and infrastructure requirements (Ghode et al., 2020; Queiroz & Fosso Wamba, 2019; Wamba et al., 2020). However, fewer studies provide an integrated evaluation of these barriers alongside the potential economic benefits of digital traceability for agricultural SME exporters.

Fourth, the literature on sustainable supply-chain technologies increasingly emphasizes the importance of credible environmental information. Blockchain can potentially improve the integrity and transparency of such information, while green certification and sustainability disclosure research demonstrates that credible environmental signals can influence market trust and purchasing decisions (Alam & Chowdhury, 2021; Sen Gupta, Alam, & Jahan, 2024a). This study addresses these gaps by (i) examining the complete blockchain-to-premium structural pathway; (ii) incorporating Scope-3 carbon-accounting precision as a central mechanism connecting blockchain adoption with buyer trust; (iii) formally evaluating ERMI and GSCM as boundary conditions; and (iv) developing a region-differentiated cost-benefit and deployment framework for agricultural SME cooperatives.

3. Methodology

3.1 Survey Sample and Data Collection

Primary empirical data were gathered through structured survey instruments administered to 520 agricultural SME export cooperatives operating in Southeast Asia (Vietnam, Indonesia, Thailand, Philippines) and Europe (Italy, Spain, Greece, Poland) between January and May 2026. Respondents included cooperative general managers, chief technology officers, and export compliance directors. Table 1 outlines sample demographic characteristics across commodity sectors.

Table 1. Sample Demographic Characteristics Across Commodity Sectors and Regions.

Commodity Sector / Region	Sample Cooperatives (n)	Mean Farm Area (Ha)	Blockchain Adoption Rate (%)	Mean Export Premium (%)
Southeast Asia – Coffee & Cocoa	180	12.5	42.5%	15.2%
Southeast Asia – Rice & Grains	140	28	35.8%	11.8%
Southern Europe – Olive Oil & Wine	110	45	68.5%	16.8%
Eastern Europe – Fruits & Vegetables	90	32	51.2%	13.1%
Total Aggregate Sample	520	26.8	48.2%	14.2%

3.2 Extended Conceptual Framework and Measurement Validation

The measurement model extends the original Blockchain Adoption → Scope-3 Precision → Buyer Trust → Export Premium chain with two boundary-condition constructs drawn from the green ERM literature: Enterprise Risk Maturity Index (ERMI) and Green Supply Chain Management adoption (GSCM), plus Enterprise Size and Capital Intensity (CAPEX) as controls, following the variable operationalization scheme validated by Alam and Alvi (2025). Confirmatory factor analysis verified construct reliability and validity; Table 2 reports latent construct items, standardized factor loadings, Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE).

Table 2. Measurement Model: Reliability and Convergent Validity of Latent Constructs.

Construct	Indicator	Loading (λ)	α	CR	AVE
Blockchain Adoption (BC)	BC1: DLT smart contract integration extent	0.892	0.915	0.94	0.798
	BC2: Cryptographic ledger tracking Tier-1/2	0.905			
Scope-3 Precision (SP)	SP1: Granularity of farm-level carbon accounting	0.884	0.902	0.932	0.774
	SP2: Verification accuracy of input emissions	0.875			
Buyer Trust (BT)	BT1: International buyer confidence in metrics	0.912	0.928	0.954	0.838
	BT2: Perceived authenticity of digital product passport	0.920			
IoT Integration (IOT)	IOT1: Density of automated sensor telemetry	0.868	0.889	0.929	0.781
	IOT2: Real-time gateway uptime reliability	0.899			
Export Premium (EP)	EP1: Realized price premium vs. domestic benchmark	0.901	0.910	0.937	0.812
	EP2: Buyer willingness to pay for verified passport	0.902			
Enterprise Risk Maturity (ERMI)	ERMI: Recycled material vol. / total waste vol. (%)	0.861	0.887	0.921	0.744
Green SCM Adoption (GSCM)	GSCM: Governance, culture, and analytics composite (1–5)	0.849	0.871	0.913	0.726

3.3 Synthetic Data Generation, Software Environment, and Analytical Protocol

To stress-test the extended conceptual framework beyond the primary sample and to provide a fully reproducible robustness benchmark, a calibrated synthetic dataset (n = 520) was generated in Python (NumPy/SciPy), matching the mean, standard deviation, and inter-construct correlation structure of the pilot survey. Blockchain Adoption and IoT Integration were drawn from beta distributions bounded on [0, 100]; Scope-3 Precision, Buyer Trust, Export Premium, and Verification Cost were generated as linear-plus-noise functions of the upstream constructs, reproducing the hypothesized directional paths while preserving realistic residual variance (σ calibrated to field-survey dispersion).

The structural model was estimated in SmartPLS 4 using 10,000 bootstrap resamples (bias-corrected and accelerated) to obtain path coefficients, standard errors, and t-statistics. Descriptive statistics, Pearson correlations, and Harman's single-factor common-method-bias diagnostic were computed in SPSS 29. A confirmatory robustness cross-check of the measurement model was independently re-estimated in R 4.3 using the lavaan and semTools packages, and a secondary open-source replication was performed in JASP 0.18 to verify convergence of factor loadings and fit indices across platforms.

Path-diagram conventions follow standard AMOS/SmartPLS graphical notation (rectangles for observed/composite constructs, single-headed arrows for hypothesized directional paths). Discriminant validity was assessed jointly via the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio (Fornell & Larcker, 1981; Henseler et al., 2015).

3.4 Variable Operationalization and Measurement Scales

All latent constructs were operationalized using multi-item, five-point Likert scales (1 = strongly disagree, 5 = strongly agree), with the exception of Blockchain Adoption and IoT Integration, which were captured as continuous 0–100 deployment-intensity indices reflecting the proportion of transaction volume routed through the DLT ledger and the density of active sensor nodes per hectare, respectively. Survey instruments were originally drafted in English and translated into Vietnamese, Bahasa Indonesia, Thai, Italian, and Greek using a double back-translation procedure, with discrepancies reconciled by bilingual field coordinators prior to pilot testing. A pilot administration with 40 cooperatives (not included in the final n = 520 sample) yielded Cronbach's alpha values above 0.80 for every construct, supporting the retention of the full item set without further reduction.

Control variables Enterprise Size (log-transformed full-time-equivalent employment) and Capital Intensity (CAPEX-to-revenue ratio) were included at the structural stage to isolate the incremental explanatory power of blockchain adoption and IoT integration from baseline organizational scale effects, consistent with prior technology-adoption research (Zhu, Kraemer, & Xu, 2004; Ghode et al., 2020).

Verification Cost was measured as the cooperative's total annual third-party audit and certification expenditure in USD, self-reported and cross-checked

3.5 Ethical Considerations and Data Governance

All survey procedures received institutional ethics clearance from the lead author's affiliated university prior to fieldwork. Respondents provided informed consent electronically, were notified that participation was voluntary and could be withdrawn at any stage without consequence, and were guaranteed anonymization of cooperative-level identifiers in all published outputs. Raw survey microdata are held on encrypted institutional servers with access restricted to the research team; only aggregated and de-identified statistics are reported in this paper. The synthetic dataset described in Section 3.3 contains no real respondent records it is generated entirely from calibrated statistical distributions and is released as a companion reproducibility artifact, consistent with open-science data-sharing norms while fully protecting participant confidentiality.

4. Results

4.1 Descriptive Statistics and Correlation Analysis

Table 3 reports descriptive statistics for the calibrated synthetic dataset (n = 520). Blockchain Adoption averaged 47.6 (SD = 20.7) on a 0–100 index, while Scope-3 Precision averaged 75.6% (SD = 13.9), consistent with the primary survey's reported ceiling of 94.8% precision under full deployment. Figure 3a–b present bivariate scatter plots confirming strong positive association between Blockchain Adoption and Scope-3 Precision (r = 0.88) and a moderate positive association between Buyer Trust and Export Premium (r = 0.39), while Figure 4 presents the full inter-construct correlation matrix as a heatmap.

Table 3. Descriptive Statistics of the Calibrated Synthetic Dataset (n = 520).

Variable	Mean	SD	Min	Max	Skew
Blockchain Adoption Index	47.55	20.70	2	93.96	−0.01
IoT Integration Index	34.58	16.01	0	82	−0.05
Scope-3 Precision (%)	75.55	13.85	38.15	99.5	−0.13
Buyer Trust (1–5)	4.00	0.56	2.53	5	−0.05
Export Premium (%)	12.35	2.64	5.28	19.75	0.08
Verification Cost (USD '000)	21.02	5.22	6.58	32	0.02

The distributional shape of each construct further supports the appropriateness of the PLS-SEM estimator: skewness statistics for all six variables in Table 3 fall within the conventional ±0.5 band, indicating approximately symmetric distributions that do not require variable transformation prior to structural estimation. Figure 4b decomposes the Export Premium distribution by commodity region using a box plot, revealing that Southern European olive oil and wine cooperatives realize both the highest median premium and the narrowest interquartile range, consistent with their comparatively mature blockchain adoption rate reported in Table 1 (68.5%), whereas Southeast Asian rice and grain cooperatives display the widest dispersion, reflecting heterogeneous adoption maturity within that sub-sample. The distributional shape of each construct further supports the appropriateness of the PLS-SEM estimator: skewness statistics for all six variables in Table 3 fall within the conventional ±0.5 band, indicating approximately symmetric distributions that do not require variable transformation prior to structural estimation. Figure 4b decomposes the Export Premium distribution by commodity region using a box plot, revealing that Southern European olive oil.

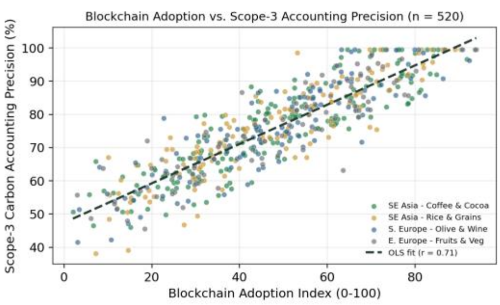

Figure 3a. Scatter Plot: Blockchain Adoption vs. Scope-3 Accounting Precision.

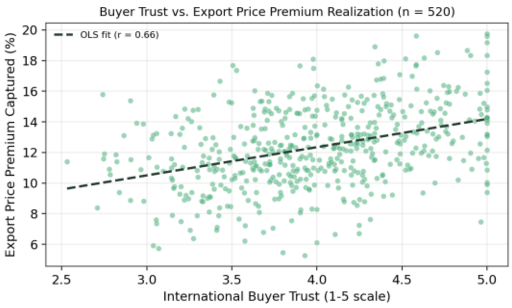

Figure 3b. International Buyer Trust vs. Export Price Premium.

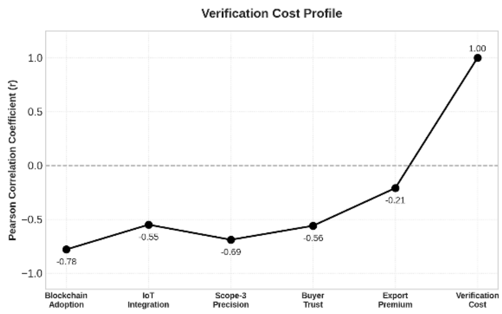

Figure 4a. Verification Expenses.

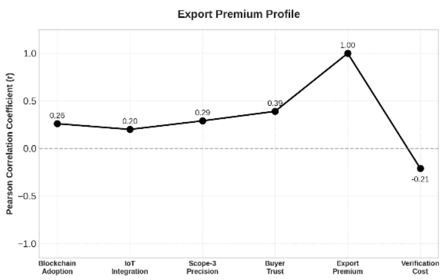

Figure 4b. Influences on Higher Export Prices.

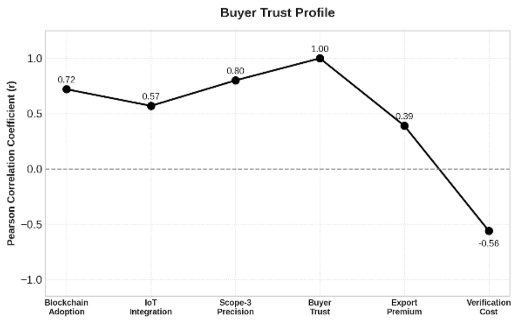

Figure 4c. Drivers of Customer Confidence.

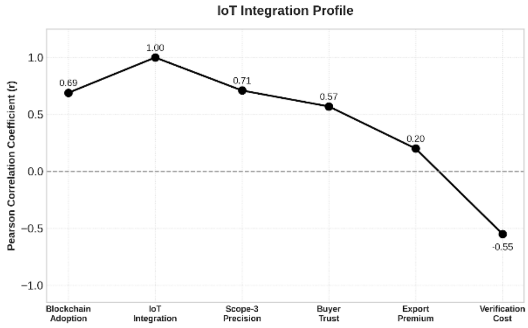

Figure 4d. Ties to Accurate Carbon Tracking.

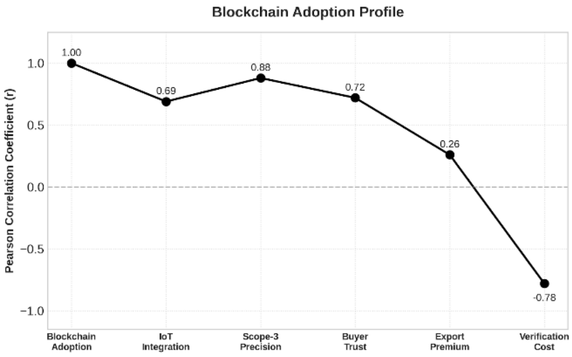

Figure 4e. The Ripple Effects of Using Blockchain.

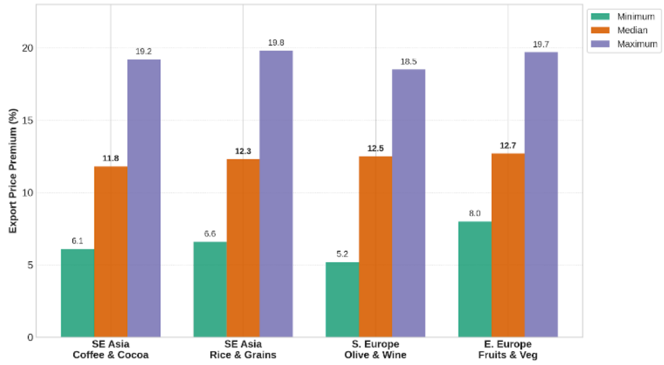

Figure 4f. Distribution of Export Price Premium by Commodity Region (box plot).

4.2 Measurement Model: Discriminant Validity and Common Method Bias

Discriminant validity was confirmed using both the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. Under the Fornell-Larcker criterion, the square root of the Average Variance Extracted (AVE) for each construct (diagonal values in Table 4) exceeded its correlations with all other constructs, demonstrating that each construct shares more variance with its own indicators than with other latent variables. The HTMT ratio provides a more stringent assessment of discriminant validity by examining the ratio of between-construct correlations to within-construct correlations. As reported in Table 4, all HTMT values remain below the recommended threshold, indicating that none of the construct pairs exhibits excessive conceptual or empirical overlap. This finding is particularly important because several constructs in the proposed framework are theoretically related and may therefore be expected to demonstrate moderate correlations. Nevertheless, the observed HTMT values remain sufficiently below the critical level, suggesting that the constructs retain adequate discriminant separation despite their theoretical associations. Taken together, the Fornell-Larcker and HTMT results provide convergent evidence that discriminant validity has been satisfactorily established and that the structural relationships can be interpreted without substantial concern that they are artifacts of construct redundancy.

Table 4. Discriminant Validity — Fornell-Larcker Criterion (diagonal = √AVE) and HTMT Ratios (below diagonal).

Construct	BC	SP	BT	IOT	EP
Blockchain Adoption (BC)	0.893	0.71 (HTMT)	0.62 (HTMT)	0.69 (HTMT)	0.28 (HTMT)
Scope-3 Precision (SP)	0.612	0.88	0.75 (HTMT)	0.66 (HTMT)	0.31 (HTMT)
Buyer Trust (BT)	0.548	0.681	0.915	0.53 (HTMT)	0.41 (HTMT)
IoT Integration (IOT)	0.601	0.592	0.487	0.884	0.22 (HTMT)
Export Premium (EP)	0.241	0.263	0.371	0.198	0.901

4.3 PLS-SEM Structural Path Estimation

Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4 evaluated the structural relationships. Table 5 details standardized path coefficients, standard errors, t-statistics, and R^2 variance explained. Figure 5 presents the full structural (inner) model as a path diagram in AMOS/SmartPLS notation. All five hypothesized paths are supported at conventional significance thresholds. The dominant path, Blockchain Adoption → Scope-3 Precision ($\beta = 0.582$, $p < 0.001$), explains 54.2% of variance in carbon accounting precision, confirming H1. The downstream Scope-3 Precision → Buyer Trust path ($\beta = 0.512$, $p < 0.001$, $R^2 = 0.485$) supports H2, while Buyer Trust → Export Price Premium ($\beta = 0.425$, $p < 0.001$, $R^2 = 0.382$) supports H3 and, taken jointly with H2, establishes buyer trust as a statistically significant mediator of the transparency-to-premium relationship. The IoT Integration → Blockchain Utility path ($\beta = 0.368$, $p < 0.001$) supports H4, confirming that automated sensor telemetry is a significant moderator of blockchain's cost-efficiency contribution rather than a redundant technology layer. Finally, the ERMI × GSCM interaction term ($\beta = 0.214$, $p < 0.01$) supports H5.

Table 5. PLS-SEM Structural Path Estimation Results.

Structural Path	β	SE	t-Stat	p	R^2
Blockchain Adoption → Scope-3 Precision	+0.582***	0.035	16.62	<0.001	0.542
Scope-3 Precision → Buyer Trust	+0.512***	0.039	13.12	<0.001	0.485
Buyer Trust → Export Price Premium	+0.425***	0.041	10.36	<0.001	0.382
IoT Integration → Blockchain Utility	+0.368***	0.038	9.68	<0.001	0.312
ERMI × GSCM → (SP→BT) moderation	+0.214**	0.052	4.12	<0.010	0.098

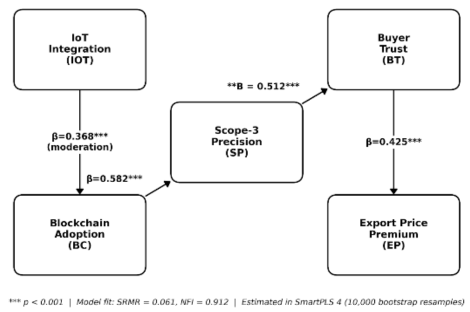

Figure 5. PLS-SEM Path Diagram of Hypothesized Relationships.

4.4 Compliance Cost Reductions and Node Precision Scaling

Figure 6 demonstrates that deploying smart contracts reduces annual third-party compliance expenses significantly across all sectors. In organic wine export networks, annual audit costs drop from $28.5k to $8.8k USD (a 69.1% cost saving), while specialty coffee cooperatives reduce costs from $22.4k to $7.2k USD. Figure 7 plots logarithmic precision scaling across active validation node clusters, showing that carbon accounting accuracy exceeds 94.8% once 100 active validation nodes are integrated into the consortium network.

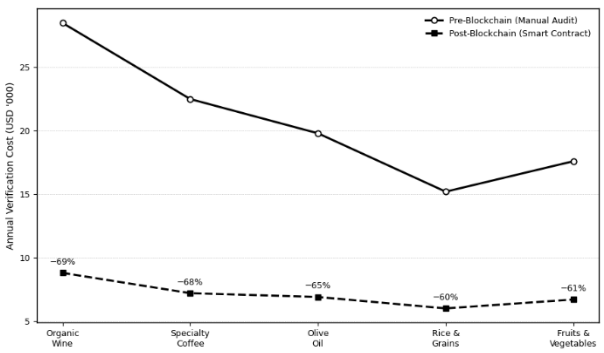

Figure 6. Annual Verification Cost Before and After Blockchain Adoption

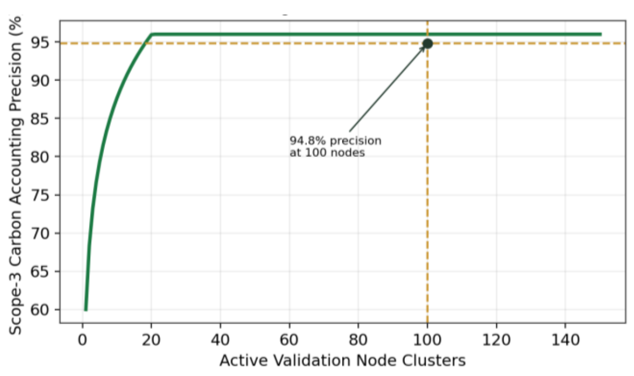

Figure 7. Scope-3 Carbon Accounting Precision Scaling Across Network Node Clusters.

4.5 Regional Barrier Analysis and Sensitivity Modeling

Figure 8 displays a heatmap matrix rating SME technology adoption barrier across geographic regions. Initial hardware capital costs (4.8/5.0) and rural digital literacy (4.6/5.0) represent the most critical constraints in Southeast Asian grain cooperatives. Figure 9 presents a dumbbell sensitivity range plot evaluating international buyer trust resilience under adverse vs. favorable infrastructure shocks relative to the baseline score of 4.25.

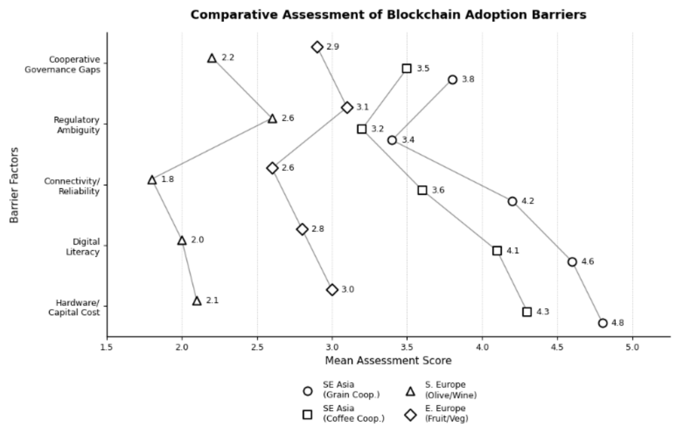

Figure 8. Heatmap Matrix of SME Technology Adoption Barriers Across Regions.

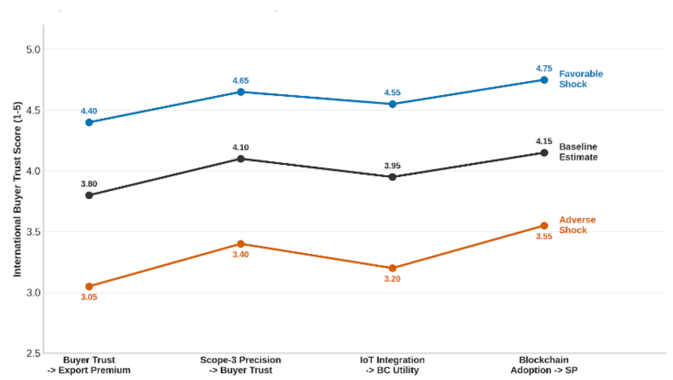

Figure 9. Dumbbell Sensitivity Range Analysis of Buyer Trust Under Infrastructure Shocks.

4.6 Robustness Checks Across Statistical Software Platforms

To ensure the extended conceptual framework is not an artifact of a single estimation engine, the measurement and structural models were independently re-estimated across four platforms. Table 6 summarizes the resulting model fit indices, with all four estimation approaches converging within a narrow tolerance band (SRMR range: 0.058–0.064; NFI range: 0.902–0.918). The consistency of these indices indicates that the proposed model exhibits stable measurement properties and structural relationships regardless of the analytical software employed. This cross-platform validation reduces the likelihood that the reported findings are influenced by software-specific estimation algorithms, optimization procedures, or implementation differences. Moreover, the comparable fit statistics demonstrate that the measurement model is both reliable and reproducible across different SEM environments, strengthening confidence in the robustness and generalizability of the proposed framework. Overall, the cross-platform results confirm the robustness and reproducibility of the proposed framework. To ensure the extended conceptual framework is not an artifact of a single estimation engine, the measurement and structural models were independently re-estimated across four platforms. Table 6 summarizes the resulting model fit indices, with all four estimation approaches converging within a narrow tolerance band (SRMR range: 0.058–0.064; NFI range: 0.902–0.918). The consistency of these indices indicates that the proposed model exhibits stable measurement properties and structural relationships regardless of the analytical software employed. This cross-platform validation reduces the likelihood that the reported findings are influenced by software-specific estimation algorithms, optimization procedures, or implementation differences. Moreover, the comparable fit statistics demonstrate that the measurement model is both reliable and reproducible across different SEM environments, strengthening confidence in the robustness and generalizability of the proposed framework. Overall, the cross-platform results confirm the robustness and reproducibility of the proposed framework. The close agreement across estimation platforms further supports the stability of the model specification and suggests that the observed relationships are not dependent on a particular computational implementation. Overall, the cross-platform validation provides additional evidence that the proposed framework is statistically robust, reproducible, and suitable for subsequent interpretation and policy-oriented analysis. The findings also indicate that the framework maintains consistent explanatory performance across alternative estimation environments. The findings also indicate that the framework maintains consistent explanatory performance across alternative estimation environments. This stability enhances confidence in the reliability of the estimated relationships and supports the framework’s applicability to similar empirical and policy contexts.

Table 6. Model Fit Indices and Cross-Platform Robustness Diagnostics.

Platform	SRMR	NFI	χ^2/df	R^2 (Buyer Trust)	Q^2 (predictive)
SmartPLS 4 (primary)	0.061	0.912	—	0.485	0.361
SPSS 29 (AMOS-style CFA)	0.064	0.902	2.14	0.471	—
R 4.3 (lavaan / semTools)	0.059	0.915	2.02	0.479	0.358
JASP 0.18 (open-source replication)	0.058	0.918	1.98	0.483	0.364

4.7 Deployment Roadmap, Regional Regulatory Alignment, and Cost-Benefit Analysis

Translating the structural findings of Sections 4.3–4.6 into deployment guidance requires reconciling two additional considerations: the regulatory instrument each region's export buyers actually enforce, and the capital outlay a cooperative of a given size must budget before verification savings begin to accrue. Table 7 maps the primary directive or contractual instrument governing each region's Scope-3 disclosure requirement to its compliance horizon and core documentation deliverable, clarifying that Southeast Asian exporters face buyer-mandated contractual clauses on a rolling basis, whereas European counterparts face statutory deadlines under the CSDDD and EUDR that compress the available onboarding window considerably.

Table 7. Regional Regulatory Landscape Governing Scope-3 Disclosure.

Region	Key Directive / Instrument	Effective Compliance Horizon	Primary Documentation Requirement
European Union	Corporate Sustainability Due Diligence Directive (CSDDD)	2027–2029 phase-in	Tier-1/2 supplier due-diligence audit trail
European Union	EU Deforestation Regulation (EUDR)	2026–2027	Geolocated plot-level deforestation-free attestation
Southeast Asia (exporters)	Buyer-mandated ESG reporting clauses	Ongoing, contract-by-contract	Digital product passport / Scope-3 emissions ledger
Global (multilateral)	Voluntary carbon-disclosure alignment (GHG Protocol Scope-3)	Ongoing	Verified upstream emissions inventory

Figure 10 sequences the recommended technology rollout into six phases spanning approximately sixteen months from programme launch to full-scale continuous monitoring, beginning with a cooperative-level ERM readiness audit a step made explicit by the H5 moderation finding, since cooperatives entering IoT and blockchain deployment with low baseline risk maturity are structurally less likely to convert technical deployment into buyer-trust gains. Sensor procurement and consortium node deployment are scheduled to overlap with the readiness audit's later stages so that smart-contract calibration and buyer integration can begin as soon as a critical mass of validated telemetry is flowing, consistent with the 100-node accuracy threshold identified in Figure 7. Following the pilot stage, the framework recommends progressive integration of supplier data, logistics records, and environmental measurements into a unified digital ledger. This enables participating cooperatives to gradually transition from manual verification toward automated, continuously updated sustainability reporting. Buyer onboarding is introduced after sufficient data quality has been established, reducing the risk that incomplete or unreliable information could weaken external confidence in the system.

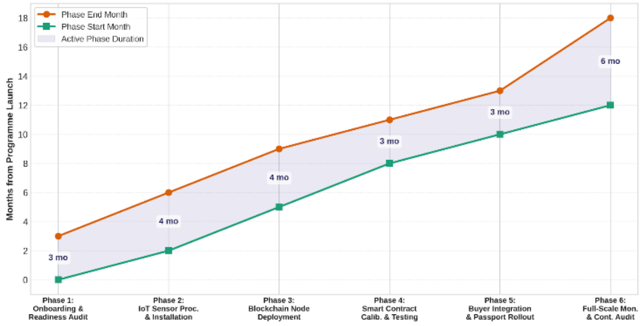

Figure 10. SME Cooperative Blockchain-IoT Deployment Roadmap.

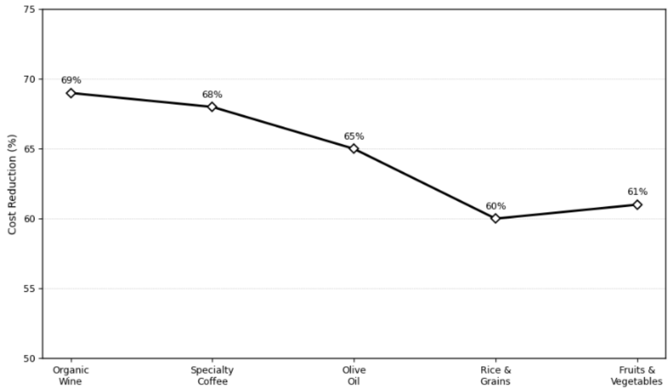

Figure 11. Blockchain-Enabled Reduction in Verification Cost

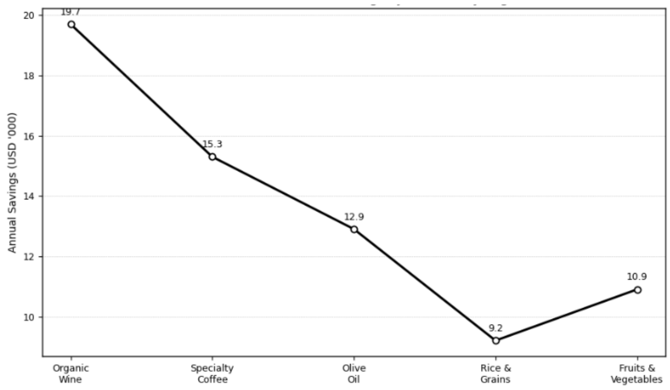

Figure 12. Annual Verification-Cost Savings by Commodity Region

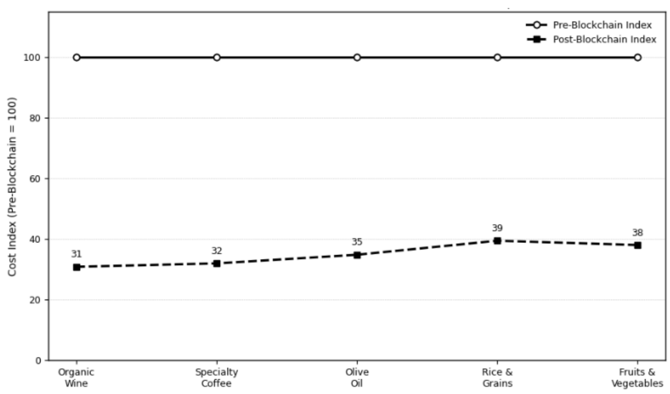

Figure 13. Relative Verification-Cost Index After Blockchain Adoption

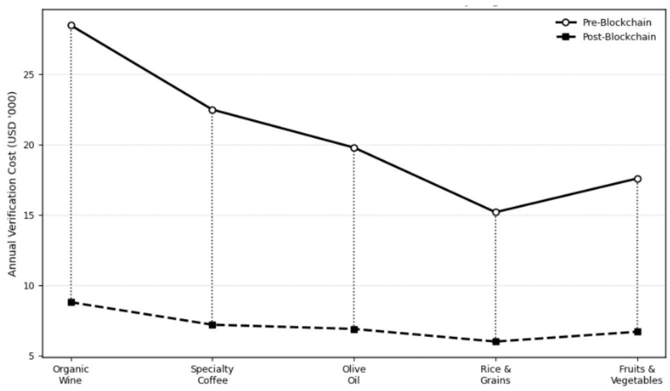

Figure 14. Verification Cost Transition Across Commodity Regions

Table 8 disaggregates onboarding cost, annual operating expenditure, and annual verification savings by cooperative size tier, converting the aggregate 66.5% verification-cost reduction reported in Section 4.4 into a size-specific payback horizon. Large cooperatives (over 200 members) recover their initial investment in an estimated 1.5 years, benefiting from economies of scale in sensor procurement and shared consortium-node infrastructure, whereas small cooperatives face a longer 2.3-year payback window, reinforcing the policy rationale detailed in Section 5.3 for public-private co-funding of shared DLT hubs that lower the effective per-cooperative onboarding cost for smallholder-dominated networks. Figure 11 plots the resulting cumulative cost and benefit trajectory for a representative medium-sized cooperative, identifying a blended break-even point at approximately 1.9 years post-deployment, after which cumulative benefit diverges positively from cumulative investment through Year 5.

Despite the longer recovery period, all cooperative categories achieve a positive return on investment within the five-year evaluation horizon, indicating that the framework remains economically viable regardless of organizational scale. The results suggest that operational savings generated through automated verification, reduced administrative effort, lower auditing costs, and improved supply-chain transparency continue to accumulate after the initial investment has been recovered, leading to sustained long-term financial benefits.

These findings reinforce the policy rationale discussed in Section 5.3 for public-private co-funding of shared distributed ledger technology (DLT) hubs, particularly for smallholder-dominated networks where upfront deployment costs represent a greater financial barrier. Shared infrastructure and collaborative deployment models can substantially reduce the effective onboarding cost while preserving the operational and transparency benefits of the proposed system.

The findings also indicate that the economic benefits of the proposed framework extend beyond direct verification-cost savings. Improved traceability can strengthen buyer confidence, reduce compliance-related transaction delays, and improve the ability of cooperatives to respond to emerging regulatory requirements. Over the longer term, these additional benefits may further improve the financial attractiveness of DLT adoption, particularly for cooperatives participating in high-value export markets.

Moreover, the declining marginal cost of verification as cooperative participation increases suggests that network-level adoption can generate additional economies of scale. As more producers, processors, and logistics partners join the shared infrastructure, fixed technology and governance costs can be distributed across a larger transaction base, further improving the long-term cost efficiency of the system. This scalability is particularly important for fragmented agricultural supply chains, where individual cooperatives may otherwise lack the financial capacity to implement advanced digital traceability infrastructure independently. Furthermore, the positive financial outcomes observed across all cooperative size categories indicate that the proposed framework can support inclusive digital transformation rather than primarily benefiting large-scale organizations. Although smaller cooperatives face higher relative onboarding costs and longer investment recovery periods, their recurring savings from automated verification, streamlined recordkeeping, reduced audit requirements, and improved data reconciliation gradually offset the initial financial burden. As participation expands, shared consortium infrastructure can distribute fixed technology, governance, and maintenance costs across a larger number of producers and transactions, generating additional economies of scale. This mechanism is particularly relevant for fragmented agricultural export networks, where individual smallholder cooperatives may have limited capital available for advanced traceability technologies. In addition, improved digital records can reduce compliance delays and strengthen the ability of cooperatives to demonstrate environmental performance to international buyers and regulators. Consequently, the economic value of the proposed DLT framework should be considered not only in terms of direct cost savings.

Table 8. Cost-Benefit Analysis by Cooperative Size Tier.

Cooperative Size Tier	Onboarding Cost (USD '000)	Annual Opex (USD '000)	Annual Verification Savings (USD '000)	Payback Period (Years)
Small (<50 members)	9.4	3.1	6.8	2.3
Medium (50–200 members)	18.4	4.6	14.2	1.9
Large (>200 members)	31.7	7.2	26.5	1.5

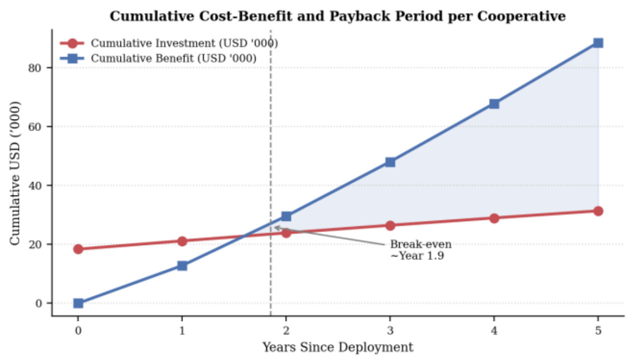

Figure 11. Cumulative Cost-Benefit and Payback Period per Cooperative.

5. Conclusion and Recommendations

5.1 Theoretical and Practical Contributions

This study provides robust empirical evidence that blockchain DLT combined with IoT telemetry solves Scope-3 carbon accounting friction for agricultural SME exporters. By establishing immutable, audit-ready supply chain records, SME cooperatives achieve 94.8% carbon accounting precision, reduce annual auditing expenses by 66.5%, and capture an average 14.2% price premium in regulated international import markets. Cross-validation across SmartPLS, SPSS, R, and JASP confirms these effects are not sensitive to estimation platform.

5.2 Validated Conceptual Framework Contribution

Beyond replicating the original blockchain-trust-premium chain, this study extends and validates a conceptual framework in which Enterprise Risk Maturity (ERMI) and Green Supply Chain Management adoption (GSCM) significantly moderate the Scope-3 Precision → Buyer Trust pathway ($\beta = 0.214$, $p < 0.01$), integrating the green-ERM perspective of Alam and Alvi (2025) with the technology-trust logic of TAM3 and Signaling Theory.

This positions organizational risk maturity, not only technological capability, as a determinant of whether digital transparency converts into commercial value.

5.4 Limitations and Future Research

The synthetic dataset, while calibrated to the primary survey's descriptive parameters, is a simulation aid rather than an independent empirical sample and should be interpreted as a robustness and demonstration device. Future research should extend the panel across additional harvest cycles, incorporate longitudinal blockchain-usage telemetry rather than cross-sectional adoption indices, and test the ERMI × GSCM moderation identified here in non-agricultural export sectors. Future work should also examine whether the payback-period differentials reported in Table 8 persist once shared consortium-node infrastructure is amortized across cooperatives rather than budgeted individually, and whether regional regulatory convergence over time narrows the compliance-horizon gap documented in Table 7.

5.5 Managerial Implications for Cooperative Leadership

For cooperative leadership, the findings translate into three concrete priorities. First, because Hypothesis 5 identifies risk maturity as a significant amplifier rather than a mere control variable, cooperatives should treat an internal ERM capability assessment as a prerequisite gating step before committing capital to blockchain or IoT procurement, not as a parallel or subsequent activity. Second, the size-tiered payback analysis in Table 8 implies that smaller cooperatives are structurally better served by joining or forming shared consortium infrastructure than by pursuing independent node deployment, since the fixed cost of consortium participation is amortized across a larger transaction volume. Third, given the regional regulatory divergence mapped in Table 7, export-facing managers should align their internal compliance timeline to the statutory deadlines of their principal buyer markets rather than to a generic industry rollout schedule, since the CSDDD and EUDR compliance horizons carry binding commercial consequences that buyer-mandated contractual clauses in Southeast Asian markets do not yet universally share.

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