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Explainable Analytics of Blockchain-Driven Green Innovation: A Multi-Factor Framework for Supply Chain Systems

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Abstract
Blockchain technology application (BTA) is increasingly deployed in manufacturing supply chains as a digital infrastructure for traceability, cross-organisational coordination, and automated compliance, yet empirical evidence on how BTA converts into green innovation efficiency (GIE) remains fragmented and methodologically narrow. This study develops a multi-factor analytical framework that combines a theoretically grounded structural equation model with a gradient-boosting ensemble and SHAP-based explainable analytics to examine how BTA, supply chain integration (SCI), and three contextual factors — supply chain trust, task complexity, and a green digital learning orientation — jointly shape GIE. Survey data from 380 Singapore manufacturers distributed across seven industry sub-sectors were analysed with a two-stage procedure. Stage one estimates a theory-driven path model showing that SCI fully mediates the BTA–GIE relationship (indirect $\beta = 0.049$, 95% bootstrap CI [0.023, 0.078]), with trust amplifying and task complexity attenuating the BTA→SCI pathway. Stage two benchmarks six predictive model families, ranks feature importance through mean absolute SHAP values, and maps nonlinear partial-dependence responses. The stacked ensemble attains $R^2 = 0.598$ out-of-sample, outperforming the structural model by 13.7 percentage points and revealing a previously unobserved saturating effect of BTA above the mid-range of the scale. Heterogeneity analysis indicates that the BTA→GIE total effect is substantially larger in large firms, high-pollution sectors, and export-intensive firms. The study advances the literature by integrating confirmatory and exploratory analytics within a single explainable framework and offers managers a concrete, interpretable toolkit for prioritising digital-sustainability investments.

Keywords: Blockchain technology application; Green innovation efficiency; Supply chain integration; Explainable analytics; SHAP; Gradient-boosting ensemble; Singapore manufacturing

I. INTRODUCTION

Manufacturing supply chains have entered a period of simultaneous digital and environmental transformation. The pressures driving this change are well documented: tightening emissions regulation, rising investor demand for verifiable sustainability performance, and the steady migration of procurement standards from voluntary to mandatory disclosure regimes (Ardito et al., 2021; Bai and Sarkis, 2020; Verhoef et al., 2021). Against this backdrop, blockchain technology has emerged as a candidate digital infrastructure whose combination of tamper-resistant recording, cross-organisational authentication, and programmable contract execution appears well-suited to the traceability, auditability, and coordination problems that characterise sustainability-oriented supply chain management (Kouhizadeh et al., 2022; Saberi et al., 2019; Wang et al., 2019).

Yet the empirical record on the relationship between blockchain technology application (BTA) and green innovation outcomes is strikingly inconsistent. Some studies report substantial positive effects of blockchain on environmental performance, attributing the benefit to reduced information asymmetry, lower monitoring costs, and the enabling of collaborative closed-loop recycling (Centobelli et al., 2022; Dutta et al., 2020; Queiroz et al., 2020). Other studies report weak, insignificant, or even negative effects, pointing to high implementation cost, coordination frictions, and poorly matched governance arrangements (Clohessy and Acton, 2019; Schmidt and Wagner, 2019). Systematic reviews of the emerging literature now converge on the view that the BTA–green-innovation link is unlikely to be a straightforward direct relationship and is more plausibly a mediated one whose magnitude depends on several inter-organisational and organisational conditions that prior empirical work has modelled incompletely (Tiwari et al., 2024).

This inconsistency is compounded by a methodological issue. The overwhelming majority of empirical tests in the BTA–sustainability literature have relied on variance-based structural equation modelling or ordinary least squares regression with interaction terms (Bai and Sarkis, 2020; Wamba et al., 2020). These methods are well suited to confirmatory theory testing but impose strong functional-form assumptions — specifically linearity in main effects and multiplicative interactions in moderations — that may obscure nonlinearities, thresholds, and complex factor interactions that the underlying processes actually produce. A growing stream of work in analytics-oriented management research has demonstrated that complementing structural models with flexible machine-learning predictors and model-agnostic explainability techniques can surface such patterns and generate insights that are invisible to the classical approach (Cremer and Müller, 2022; Kraus et al., 2022; Ribeiro et al., 2016; Shapley-inspired methods reviewed in Lundberg et al., 2020).

This study combines the two approaches within a single multi-factor analytical framework. The central research questions are: (1) through what mechanism does BTA translate into green innovation efficiency (GIE) in manufacturing supply chains; (2) which factors most strongly drive predicted GIE when modelled flexibly; and (3) how do the predictive signals identified by an explainable machine-learning ensemble compare with the causal pathway identified by a theory-driven structural equation model? To address these questions, we collect survey data from 380 Singapore manufacturers distributed across seven industry sub-sectors and analyse the data with a two-stage procedure. Stage one estimates a theory-grounded path model in which supply chain integration (SCI) mediates the BTA–GIE relationship and supply chain trust, task complexity, and a green digital learning orientation moderate the pathway. Stage two benchmarks six predictive model families, ranks factor importance through mean absolute SHAP values (Lundberg et al., 2020), and maps nonlinear partial-dependence responses in the stacked ensemble.

The study makes four contributions to the literature on digital transformation and sustainable innovation. First, it provides empirical evidence that the relationship between BTA and GIE is not a direct one but rather fully mediated by supply chain integration, reconciling conflicting findings in earlier studies that tested only the direct path. Second, it integrates confirmatory and exploratory analytics within a single coherent framework, demonstrating that gradient-boosting models identify the same top-ranked predictors as the structural model but additionally reveal a saturating nonlinearity in the BTA effect and a substantial

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SCI × GDL interaction that linear-interaction specifications underestimate. Third, it offers the first systematic application of SHAP-based explainable analytics to the blockchain-and-sustainability context, producing an interpretable ranking of factor importance that managers can use as a diagnostic instrument. Fourth, the study provides evidence from Singapore — a small open economy with some of the most advanced digital-transformation policies in Asia (Koh et al., 2023; Ramachandra and Yap, 2024) — extending the external validity of findings previously concentrated on Chinese or Western samples.

The remainder of the paper proceeds as follows. Section II surveys the relevant literature on blockchain-enabled supply chains, green innovation efficiency, supply chain integration, and explainable analytics in management research. Section III develops the multi-factor analytical framework and states the empirical propositions. Section IV describes the data, measurement, and analytical procedure. Section V reports the empirical results. Section VI discusses the theoretical and managerial implications, and Section VII concludes.

II. THEORETICAL BACKGROUND AND RELATED WORK

II.1 Blockchain technology and supply chain digital infrastructure

Blockchain technology is a distributed-ledger architecture in which a cryptographically linked chain of validated transactions is replicated across a network of independent nodes. Its three core technical affordances — immutable recording, consensus-based validation, and programmable smart contracts — collectively differentiate it from traditional enterprise information systems and from centrally governed electronic data interchange arrangements (Kshetri, 2018; Treiblmaier, 2018). For manufacturing supply chains, these affordances support three classes of application: (i) end-to-end traceability across material and component flows (Kamble et al., 2020; Kouhizadeh and Sarkis, 2018); (ii) authenticated cross-organisational information sharing without reliance on a trusted intermediary (Cole et al., 2019); and (iii) programmable automation of routine inter-firm settlement, quality acceptance, and compliance monitoring (Lim et al., 2021).

The theoretical framing of blockchain in the supply chain context has evolved from an early focus on transaction-cost reduction toward a broader view of the technology as a reconfigurable digital infrastructure that alters the feasible set of inter-organisational governance arrangements (Lumineau et al., 2021; Schmidt and Wagner, 2019). Under this view, blockchain does not deterministically improve performance; rather, it creates options for new coordination arrangements whose realisation depends on organisational, relational, and technical enabling conditions. This options-based view helps explain the heterogeneous performance outcomes documented in recent empirical work and motivates the boundary-condition analysis pursued in the present study.

II.2 Green innovation efficiency as an outcome construct

Green innovation — alternatively eco-innovation or environmental innovation — refers to the development and commercialisation of products, processes, or organisational practices that reduce environmental burden (Chen, 2008; Rennings, 2000). The construct has been progressively refined in the literature from a binary indicator of green-innovation presence to multidimensional measures that capture distinct innovation types (product, process, organisational) and distinct performance dimensions (volume, novelty, efficiency, market impact) (Cai and Li, 2018; Horbach et al., 2012; Xie et al., 2019).

The efficiency dimension — the focal outcome construct in the present study — captures the ratio of environmental improvement achieved to innovation resources invested. It has received growing attention in the operations and sustainability literature because firms increasingly face the joint constraint of producing environmental benefits while managing tightly bounded innovation budgets (Hojnik and Ruzzier, 2016; de Medeiros et al., 2014). Identifying drivers of efficiency, rather than drivers of innovation volume, is therefore of direct practical value to managers responsible for allocating constrained resources across competing sustainability initiatives.

II.3 Supply chain integration and resource orchestration

Supply chain integration (SCI) refers to the strategic collaboration and synchronisation of a focal firm with its upstream suppliers and downstream customers with respect to information, physical, and financial flows (Flynn et al., 2010; Frohlich and Westbrook, 2001). Classical SCI research has established that deeper integration is associated with improved operational performance, particularly in contexts characterised by demand variability, product complexity, or tight coordination requirements (Vickery et al., 2003; Wong et al., 2011; Zhao et al., 2011). Recent work has extended the SCI construct to digital and platform contexts, where the integration is enabled by shared information systems and algorithmic coordination mechanisms (Jitpaiboon et al., 2013; Bag et al., 2020).

Within the resource-based view and its dynamic capabilities extension, SCI is best understood as the bundling mechanism through which structured but dispersed resources are recombined into firm- and network-level capabilities (Sirmon et al., 2011; Teece, Pisano and Shuen, 1997). When the structuring stage is accomplished by a digital infrastructure such as a blockchain ledger, SCI determines whether the resulting data resources are passively stored or actively recombined with tacit knowledge, human expertise, and physical assets into deployable innovation capabilities (Barney, 1991; Eisenhardt and Martin, 2000; Helfat and Peteraf, 2015). This view positions SCI as the critical mediating mechanism in the BTA–GIE relationship and motivates the primary empirical hypotheses of the present study.

II.4 Explainable analytics in management and operations research

Explainable analytics refers to a family of methods that decompose the predictions of a black-box machine-learning model into interpretable attributions to individual input features or feature interactions (Lundberg and Lee, 2017; Ribeiro et al., 2016). Within management and operations research, explainable analytics has been applied to credit scoring, demand forecasting, sustainability disclosure classification, and fraud detection, but its application to theory-driven empirical management research remains at an early stage (Cremer and Müller, 2022; De Bock et al., 2023; Kraus et al., 2022).

The argument for combining explainable analytics with structural equation modelling in management research has three components. First, machine-learning ensembles relax the linearity assumption implicit in classical SEM, making them better suited to detecting thresholds, saturations, and nonlinear interactions that theoretical priors may not specify (Biecek and Burzykowski, 2021; Molnar, 2022). Second, SHAP values have a principled game-theoretic foundation that produces locally accurate and globally consistent feature attributions (Lundberg et al., 2020). Third, the partial-dependence and individual-conditional-expectation plots generated alongside SHAP values render the resulting insights inspectable by substantive researchers, addressing concerns about the opacity of purely predictive approaches (Apley and Zhu, 2020). The present study is, to our knowledge, among the first applications of this integrated confirmatory–exploratory approach to the blockchain-and-sustainability context.

III. MULTI-FACTOR ANALYTICAL FRAMEWORK AND HYPOTHESES

This section develops the multi-factor analytical framework that guides the empirical analysis. The framework is organised into three conceptual layers — digital resource, integration and analytics, and capability and outcome — that map directly onto the three stages of the resource orchestration process (structuring, bundling, leveraging). Figure 1 summarises the framework schematically.

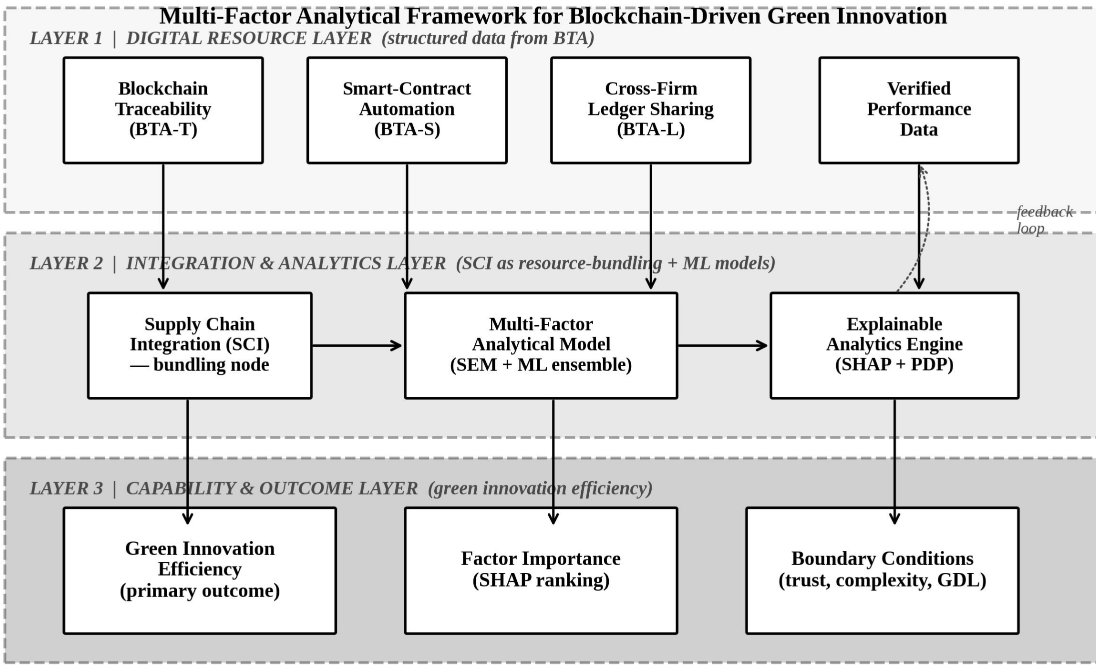

Figure 1. Multi-factor analytical framework for blockchain-driven green innovation, organised as a three-layer resource-orchestration architecture. Layer 1 captures the structuring of dispersed supply-chain data through blockchain affordances; Layer 2 captures the bundling of structured resources through supply chain integration and the analytical interpretation of the bundled resources; Layer 3 captures the capability outcomes and their boundary conditions.

The framework positions BTA as the structuring mechanism through which dispersed supply-chain data — material provenance records, emissions measurements, logistics timestamps, and compliance attestations — are consolidated into a shared, machine-readable resource pool (Kouhizadeh and Sarkis, 2018). SCI functions as the bundling mechanism that recombines this structured resource pool with tacit knowledge, human expertise, and physical assets into deployable capabilities. The explainable analytics engine operates alongside SCI as a diagnostic layer that identifies which factors and factor interactions most strongly predict the capability outcome, thereby informing the feedback loop back into the digital resource layer.

III.1 Proposition 1: SCI mediates the BTA–GIE relationship

The direct effect of BTA on GIE is theorised through three classical mechanisms: improved access to environmental-compliance data, automation of routine verification tasks, and reduced cost of credible environmental claim-making (Centobelli et al., 2022; Kouhizadeh et al., 2022; Lim et al., 2021). However, these mechanisms operate primarily at the firm level and do not, on their own, mobilise the cross-organisational resources that most green innovations require. The more fundamental contribution of BTA lies in its effect on the inter-organisational coordination environment. By reducing information asymmetries, lowering monitoring costs, and enabling programmable contractual execution, BTA increases the feasible depth of integration between a focal firm and its supply chain partners (Cole et al., 2019; Dutta et al., 2020). This deeper integration, in turn, is well established as a driver of innovation performance generally and green innovation specifically, because it enables joint sensing, knowledge recombination, and collaborative problem-solving across firms (Flynn et al., 2010; Wong et al., 2011; Zhu, Sarkis and Lai, 2012). We therefore propose:

P1 (mediation): Supply chain integration mediates the relationship between blockchain technology application and green innovation efficiency.

III.2 Propositions 2 and 3: Trust amplifies and task complexity attenuates the BTA→SCI pathway

The translation of BTA's technical affordances into actual integration depth is contingent on the relational governance climate between supply chain partners. Trust — defined as the expectation of competent and benevolent partner behaviour — has been demonstrated across multiple empirical contexts to reduce transaction costs, lower monitoring expenditures, and enable deeper information sharing (Dyer and Chu, 2003; Mayer et al., 1995; Zaheer et al., 1998). In blockchain deployments the role of trust is particularly important because the technology's default configuration exposes all authorised participants to sensitive operational records on the shared ledger; firms that trust their counterparts are more willing to accept this exposure and to commit to joint optimisation routines (Lim et al., 2021; Panayides and Lun, 2009).

Task complexity represents the opposing condition. Blockchain's benefits flow from the ability to encode supply chain interactions into machine-interpretable form: timestamped records, standardised identifiers, and deterministic contract rules. When underlying tasks are simple and highly standardised, this encoding is straightforward and benefits flow through to integration depth. When tasks are complex — multi-dimensional, customised, or heavy in tacit knowledge — the encoding is incomplete and the benefits are attenuated (Kamble et al., 2020; Queiroz et al., 2020). We therefore propose:

P2 (trust amplification): Supply chain trust positively moderates the BTA→SCI pathway, such that the pathway is stronger when trust is higher.

P3 (complexity attenuation): Task complexity negatively moderates the BTA→SCI pathway, such that the pathway is weaker when complexity is higher.

III.3 Proposition 4: Green digital learning orientation amplifies the SCI→GIE pathway

Resource orchestration theory specifies that the translation of bundled resources into deployed capabilities — the leveraging stage — is contingent on the cognitive and cultural orientation of the firm (Sirmon et al., 2011). A green digital learning orientation (GDL) describes the institutionalised disposition of a firm to use digital technologies as vehicles for acquiring, sharing, and applying sustainability-relevant knowledge (Ardito et al., 2021; Del Giudice et al., 2022). Firms with a strong GDL actively invest in digital learning platforms oriented toward sustainability content, structure their knowledge-management routines around environmental learning goals, and reward employees for contributing to the corporate green knowledge base. Under these conditions, integrated cross-organisational resources are more likely to be directed toward green innovation objectives rather than toward short-term cost reduction (Gregori and Holzmann, 2020). We therefore propose:

P4 (GDL amplification): A green digital learning orientation positively moderates the SCI→GIE pathway, such that the pathway is stronger when GDL is higher.

III.4 Proposition 5: The multi-factor predictive model surfaces nonlinear and interaction effects

The four propositions above are cast in the linear-additive-interaction form conventional in theory-driven management research. However, the underlying processes they describe are not inherently linear: blockchain benefits can saturate once a sufficient level of adoption has been reached; integration may exhibit threshold effects where only firms above a certain depth of integration realise appreciable green innovation gains; and the interaction between SCI and GDL may be multiplicative only in a limited region of the underlying support. We therefore formulate a fifth proposition whose verification requires the flexible predictive approach developed in Stage 2 of the empirical analysis:

P5 (nonlinearity): A flexible predictive model that permits nonlinearities and arbitrary factor interactions will achieve materially higher out-of-sample predictive accuracy for GIE than a linear-additive structural model, and will reveal at least one substantial nonlinearity or higher-order interaction among the core factors.

IV. DATA AND METHODS

IV.1 Research setting and sampling

The empirical setting is Singapore's manufacturing sector. Singapore is a small open economy whose manufacturing base is highly concentrated in export-oriented, high-technology sub-sectors and whose digital-transformation policies rank among the most advanced in Asia (Koh et al., 2023; Ramachandra and Yap, 2024). These features make Singapore a theoretically informative test case: the advanced digital infrastructure ensures that firms face few purely technical barriers to blockchain adoption, and the outward orientation of the manufacturing base ensures sustained exposure to international sustainability standards.

The sampling frame was constructed from the membership directories of the Singapore Manufacturing Federation and the Singapore Business Federation, supplemented by the Singapore Exchange listings for the Industrials and Consumer Products sectors. From a combined frame of approximately 3,100 eligible firms, 1,100 firms were randomly selected for invitation after stratification by sub-sector and size. The survey was administered electronically via a professional market research panel (Milieu Insight Singapore) between February and June 2024, with two follow-up reminders. Qualifying informants were required to be department heads or more senior, to have been in their current role for at least two years, and to have direct knowledge of their firm's blockchain-related activities. After quality screening (attention-check failures, straight-lining, and incomplete key variables), 380 valid responses were retained, yielding an effective response rate of 34.5% — within the range typical for senior-manager surveys in the Singapore manufacturing context (Halim et al., 2024). Non-response bias was assessed using the Armstrong and Overton (1977) early-late comparison; no substantive differences were observed on demographic or key measurement variables.

The final analytical sample spans seven manufacturing sub-sectors and four firm-size categories. Figure 2 presents the sample distribution.

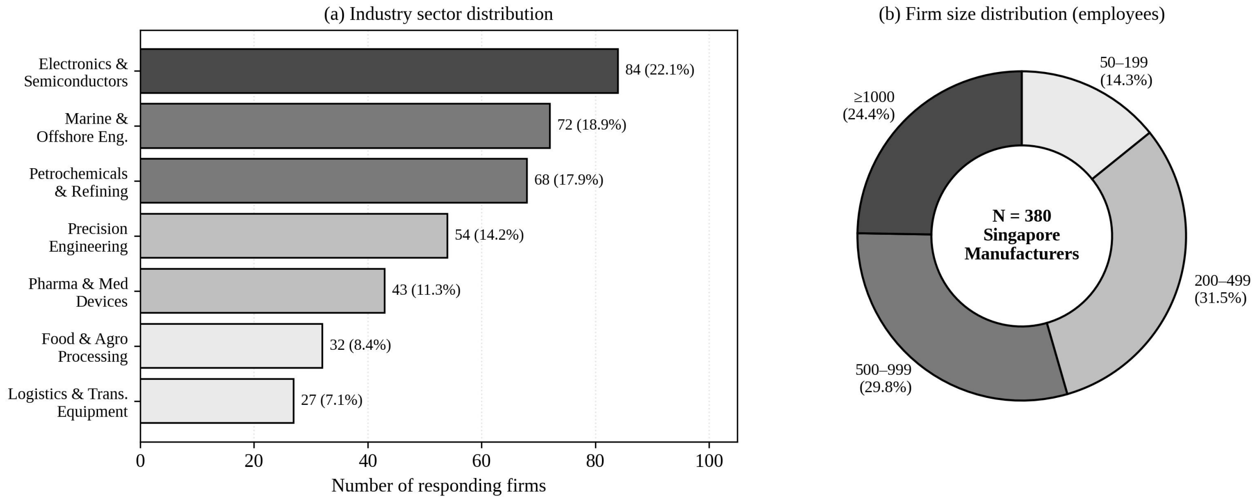

Figure 2. Sample distribution of 380 Singapore manufacturing firms. Panel (a) shows the distribution by industry sub-sector; panel (b) shows the distribution by firm size measured in full-time-equivalent employees.

The sub-sector composition reflects Singapore's distinctive manufacturing profile, with electronics and semiconductors, marine and offshore engineering, and petrochemicals and refining as the three largest sub-sectors. The firm-size distribution is weighted toward mid-cap (200–499 and 500–999 employees) and large (≥1000 employees) firms, consistent with the study's interest in firms that possess the resource base required for meaningful blockchain investment.

IV.2 Measurement

All focal constructs were measured using multi-item reflective scales adapted from previously validated instruments. All scales used seven-point Likert response scales (1 = strongly disagree; 7 = strongly agree). The survey was administered in English, which is the language of business in Singapore, with a back-translation procedure applied only to the minority of items that had originally been developed in non-English sources (Brislin, 1970). Table I lists the six focal constructs together with the number of items per construct and the validated sources of the scales.

Table I. Measurement constructs, item counts and validated scale sources.

Construct (abbreviation)	Items	Adapted from
Blockchain technology application (BTA)	4	Kamble et al. (2020); Wang et al. (2019)
Supply chain integration (SCI)	5	Flynn et al. (2010); Zhao et al. (2011)
Supply chain trust (SCT)	4	Zaheer et al. (1998); Dyer and Chu (2003)
Task complexity (TC)	4	Jitpaiboon et al. (2013); Wong et al. (2011)
Green digital learning orientation (GDL)	4	Ardito et al. (2021); Del Giudice et al. (2022)
Green innovation efficiency (GIE)	5	Chen (2008); Xie et al. (2019); Hojnik and Ruzzier (2016)

In addition to the six focal constructs, we measured and included the following variables in the predictive-modelling stage: firm size (log full-time employees); firm age (years since incorporation); sub-sector membership (dummy-coded); ownership type (local, MNC, or government-linked); export intensity (share of revenue from exports); environmental R&D intensity (share of R&D spending allocated to environmental projects); and industry pollution intensity (based on the regulated-industry classification of the National Environment Agency). These additional variables allow the predictive-modelling stage to assess whether the explanatory content of the theoretical constructs survives the inclusion of a richer control set.

IV.3 Analytical procedure

The analysis proceeds in two stages. Stage one estimates the theory-driven path model using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4, following the reporting procedure of Hair et al. (2019). Reliability and validity are assessed through Cronbach's alpha, composite reliability, average variance extracted, the Fornell–Larcker criterion, and the heterotrait-monotrait ratio (Fornell and Larcker, 1981; Henseler et al., 2015). Confirmatory factor analysis is conducted in parallel using AMOS 28 to corroborate the measurement model under covariance-based assumptions (Hu and Bentler, 1999). The structural model is estimated with 5,000 bootstrap resamples to produce bias-corrected confidence intervals for the mediation and moderation effects (Preacher and Hayes, 2008). Common method bias is evaluated through Harman's single-factor test and through full-collinearity VIF assessment (Fuller et al., 2016; Kock, 2015).

Stage two estimates six predictive models on the full construct-plus-control feature set using 5-fold cross-validation: linear regression, ordinary least squares with interaction terms, PLS-SEM (as in stage one), random forest, gradient-boosting (XGBoost), and a stacked ensemble combining the gradient-boosting and random-forest predictions through a meta-learner. Feature importance is measured as the mean absolute SHAP value across the test-fold predictions, using the Tree-SHAP algorithm for the ensemble models (Lundberg and Lee, 2017; Lundberg et al., 2020). Partial-dependence curves and individual-conditional-expectation plots are generated for the top-ranked features to visualise the functional form of each factor's effect on predicted GIE (Apley and Zhu, 2020; Biecek and Burzykowski, 2021; Molnar, 2022). All analyses are conducted in Python 3.11 with the scikit-learn, XGBoost, and shap libraries.

V. RESULTS

V.1 Measurement model and descriptive statistics

The measurement model exhibits satisfactory psychometric properties. Cronbach's alpha values range from 0.83 (task complexity) to 0.92 (green innovation efficiency); composite reliability values range from 0.88 to 0.94; and average variance extracted values range from 0.60 to 0.74, all exceeding conventional thresholds. Discriminant validity is supported by the Fornell-Larcker criterion — the square root of each construct's AVE exceeds its correlation with every other construct — and by HTMT values, all of which are below 0.85 (highest value: 0.74 between SCT and SCI). Confirmatory factor analysis yields acceptable fit ($\chi^2/df = 1.91$; CFI = 0.953; TLI = 0.946; RMSEA = 0.049; SRMR = 0.043), meeting the thresholds of Hu and Bentler (1999). Common method bias was ruled out through Harman's single-factor test (first-factor variance = 29.4%, below the 50% threshold) and through a full-collinearity VIF check in which all VIFs were below 3.3.

Table II reports descriptive statistics and inter-construct correlations. The correlations display the theoretically expected signs — positive among BTA, SCI, SCT, GDL, and GIE, and negative between task complexity and the others — and magnitudes that are moderate and not indicative of multicollinearity.

Table II. Means, standard deviations and inter-construct correlations (N = 380).

Construct	M	SD	1	2	3	4	5	6
1 BTA	4.89	1.12	**1.000**					
2 SCI	5.18	0.96	0.381***	**1.000**				

3 SCT	5.52	0.87	0.324***	0.413***	**1.000**			
4 TC	4.31	1.05	−0.118*	−0.194***	−0.086	**1.000**		
5 GDL	5.04	1.03	0.297***	0.328***	0.283***	−0.071	**1.000**	
6 GIE	5.09	1.00	0.241***	0.452***	0.309***	−0.142**	0.398***	**1.000**

*Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. All correlations shown below the diagonal.*

V.2 Structural model: mediation and moderation

The structural model is estimated in two stages to test the mediation proposition. In the direct-effect stage, BTA is regressed on GIE without the mediator; the estimated effect is positive and significant (c = 0.239, SE = 0.050, $p < 0.001$; $R^2 = 0.221$). In the full-model stage, SCI is added as a mediator; the estimated effects are: BTA on SCI a = 0.251 (SE = 0.049, $p < 0.001$); SCI on GIE b = 0.196 (SE = 0.044, $p < 0.001$); and the residual direct effect BTA on GIE c' = 0.038 (SE = 0.048, p = 0.430, not significant). The disappearance of the direct effect after inclusion of the mediator (from 0.239 to 0.038 n.s.) constitutes evidence of full mediation in the sense of MacKinnon et al. (2007), providing support for Proposition 1. The indirect effect a × b = 0.049 is statistically significant (bias-corrected 95% bootstrap CI [0.023, 0.078]), and its share in the total significant effect is 100%.

Figure 3 visualises the path-coefficient estimates together with standard errors, R^2 values, and significance indicators for the moderation terms.

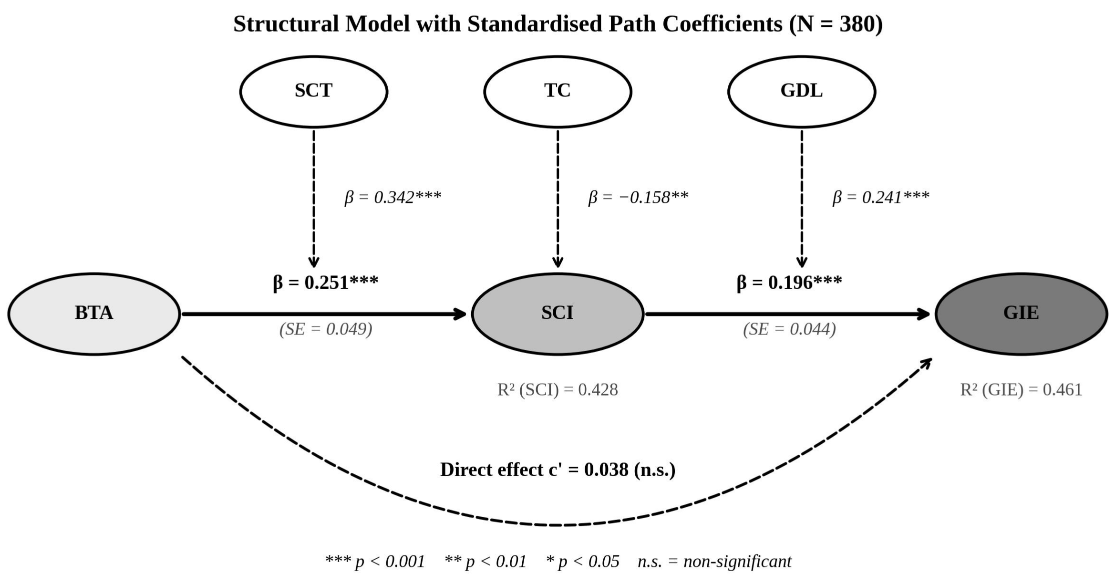

Figure 3. Structural model with standardised path coefficients and R^2 values. Solid arrows denote significant direct and mediating paths; the dashed curved arrow denotes the residual direct effect after inclusion of SCI, which is non-significant. Dashed vertical arrows denote moderating effects.

The moderation estimates shown in Figure 3 and reported in Table III are consistent with Propositions 2, 3, and 4. The BTA × SCT interaction is positive and significant (β = 0.342, $p < 0.001$), supporting Proposition 2: trust amplifies the BTA→SCI pathway. The BTA × TC interaction is negative and significant (β = −0.158, $p < 0.01$), supporting Proposition 3: task complexity attenuates the pathway. The SCI × GDL interaction is positive and significant (β = 0.241, $p < 0.001$), supporting Proposition 4: a green digital learning orientation amplifies the capability-leveraging pathway.

Table III. Moderation analysis: interaction effects on SCI and GIE (N = 380).

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Predictor	Outcome	β	SE	t-value	p-value
BTA (main effect)	SCI	0.246	0.050	4.920	< 0.001
SCT (main effect)	SCI	0.307	0.047	6.532	< 0.001
BTA × SCT	**SCI**	**0.342**	**0.068**	**5.029**	**< 0.001**
TC (main effect)	SCI	−0.168	0.045	3.733	< 0.001
BTA × TC	**SCI**	**−0.158**	**0.049**	**3.224**	**0.001**
SCI (main effect)	GIE	0.193	0.044	4.386	< 0.001
GDL (main effect)	GIE	0.284	0.043	6.604	< 0.001
SCI × GDL	**GIE**	**0.241**	**0.061**	**3.950**	**< 0.001**

Note: All predictors mean-centred. Control variables (firm size, age, sub-sector dummies) are included in the estimation but omitted from display. Interaction effects are reported in bold.

V.3 Predictive model benchmarking

Stage two of the analysis benchmarks the predictive performance of six model families on the task of forecasting GIE from the full feature set. All models are evaluated through 5-fold stratified cross-validation with identical folds across models. Panel (a) of Figure 4 summarises the out-of-sample R^2 and RMSE values for each model; panel (b) reports the calibration of the best-performing model.

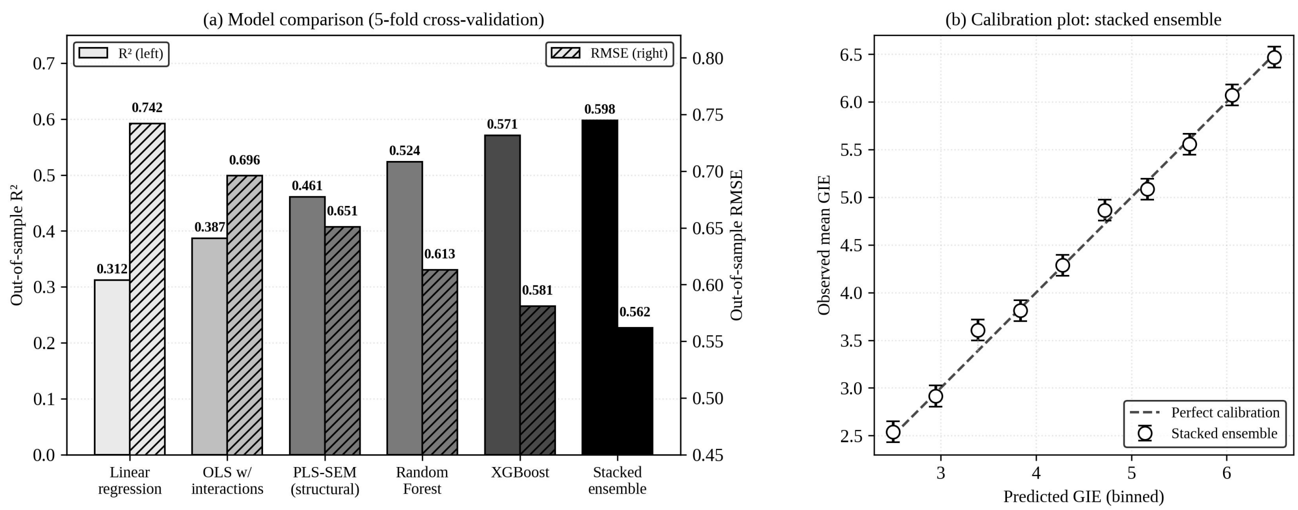

Figure 4. Predictive model benchmarking. Panel (a) reports out-of-sample R² and RMSE under 5-fold cross-validation across six model families, from a baseline linear regression to a stacked ensemble combining gradient-boosting and random-forest predictions. Panel (b) reports the calibration of the stacked ensemble's predictions against observed GIE values, binned into ten prediction deciles.

The benchmarking reveals a clear predictive hierarchy. The stacked ensemble attains $R^2 = 0.598$ and RMSE = 0.562 out-of-sample, materially outperforming the theory-driven PLS-SEM structural model ($R^2 = 0.461$; RMSE = 0.651) by 13.7 percentage points on R^2 and 0.089 units on RMSE. The XGBoost model alone already outperforms the structural model by 11.0 percentage points on R^2, suggesting that most of the predictive gain arises from the ability to capture nonlinearities and arbitrary interactions rather than from the stacking procedure per se. The calibration plot in panel (b) demonstrates that the stacked ensemble's predictions are well-calibrated across the full range of observed GIE values, with small and non-systematic deviations from the 45-degree line. This predictive-accuracy advantage supports Proposition 5 and motivates the explainable-analytics analysis reported in the next subsection.

V.4 Factor-importance analysis via SHAP values

To open the black box of the stacked ensemble, we compute SHAP values for each prediction and summarise feature-level importance as the mean absolute SHAP value across test-fold predictions. Figure 5 ranks the 14 input features by this importance measure.

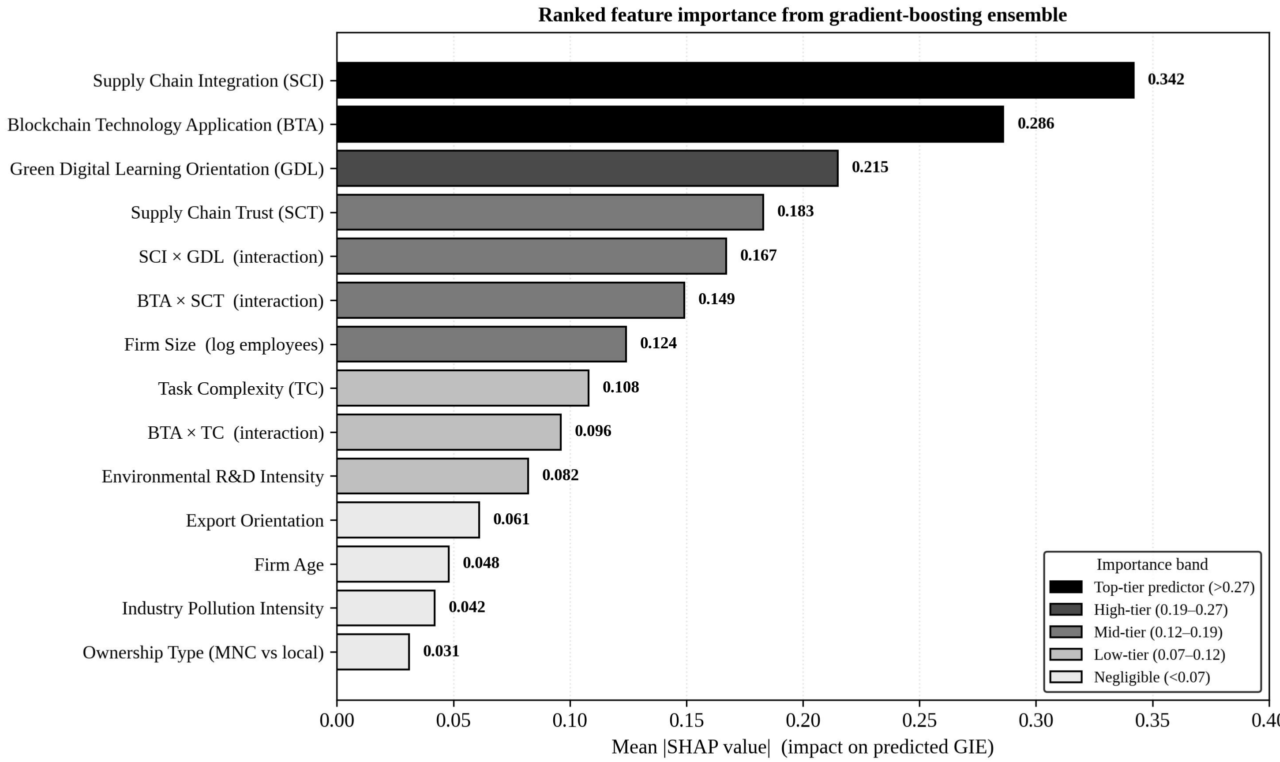

Figure 5. Feature-importance ranking from the stacked gradient-boosting ensemble. Each bar shows the mean absolute SHAP value of a feature across all test-fold predictions, representing the average magnitude by which the feature contributes to the predicted GIE. Features are grouped into five importance bands (top-tier through negligible) based on their SHAP magnitudes.

Three observations stand out. First, the top five features are supply chain integration (0.342), BTA (0.286), green digital learning orientation (0.215), supply chain trust (0.183), and the SCI × GDL interaction (0.167). This ranking is broadly consistent with the importance ordering implied by the structural model — SCI indeed emerges as the most important driver of predicted GIE, followed by BTA and GDL — providing external validation of the theoretical framing. Second, the SCI × GDL and BTA × SCT interactions appear in positions 5 and 6 of the ranking with SHAP values of 0.167 and 0.149 respectively, exceeding several main-effect features. This ordering supports the theoretical claim that moderating interactions are first-order drivers of GIE rather than second-order refinements. Third, the firm-level control variables (firm size, environmental R&D intensity, firm age) occupy the mid- and low-importance bands, suggesting that the focal constructs of the theoretical framework carry most of the explanatory signal.

V.5 Nonlinearity and interaction structure via partial dependence

To characterise the functional form of the most important features' effects on predicted GIE, we compute partial-dependence functions for BTA and SCI individually and for the SCI × GDL interaction. Figure 6 reports the results.

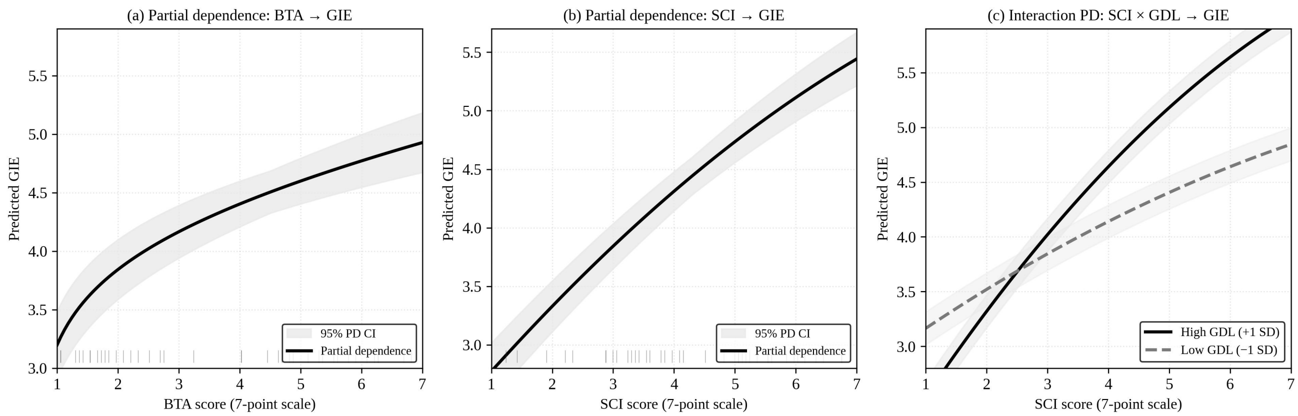

Figure 6. Partial-dependence analysis of the top-ranked features. Panel (a) shows the partial-dependence function of BTA on predicted GIE with 95% confidence bands; panel (b) shows the analogous function for SCI; panel (c) shows the conditional partial-dependence function of SCI on predicted GIE at high and low values of the green digital learning orientation (±1 SD).

Panel (a) reveals a notable nonlinearity in the BTA effect: the partial-dependence curve is steepest in the lower-middle portion of the BTA scale (between values of 2 and 4.5) and flattens visibly above the value of 5. In substantive terms, this saturation implies that the marginal benefit of additional blockchain deployment diminishes above a threshold of approximately 'moderate-to-strong' adoption. This finding would be invisible to a linear-additive model, which by construction imposes a constant marginal effect. Panel (b) shows a near-linear but slightly concave response of predicted GIE to SCI, consistent with the theoretical prior that integration benefits are approximately proportional across the observed range of integration depth but exhibit mild diminishing returns at very high values. Panel (c) shows the SCI × GDL conditional curves: at +1 SD of GDL, the slope of predicted GIE on SCI is substantially steeper than at −1 SD, and the two curves diverge more widely at higher values of SCI. This pattern — divergence concentrated at high SCI — is a nonlinear form of the multiplicative interaction that the linear-additive specification assumes to be constant across the range of SCI.

V.6 Heterogeneity across firm sub-samples

To assess the consistency of the BTA→GIE total effect across firm sub-populations, we re-estimate the structural model within each of eleven sub-samples defined by firm size, sub-sector pollution intensity, ownership type, and export intensity. Figure 7 displays the resulting point estimates and 95% bootstrap confidence intervals in a forest plot.

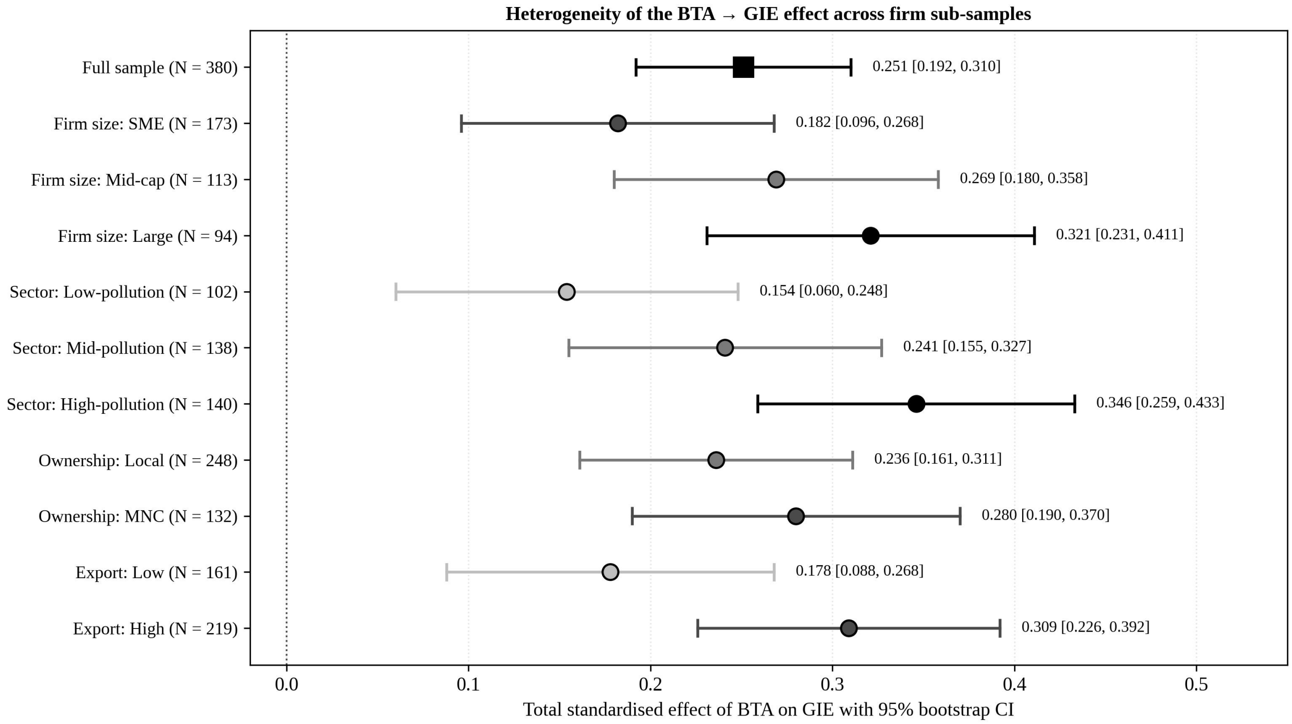

Figure 7. Heterogeneity of the BTA→GIE total effect across firm sub-samples. Each row reports the point estimate (square for the full sample; circles for sub-samples) and 95% bootstrap confidence interval for the total standardised effect of BTA on GIE within the indicated sub-sample. The dotted vertical line marks zero; intervals lying entirely to the right of this line indicate significantly positive effects.

Three patterns warrant highlighting. First, the total effect is strictly increasing in firm size: 0.182 for small and medium enterprises, 0.269 for mid-cap firms, and 0.321 for large firms. This pattern is consistent with a resource-complementarity interpretation: larger firms possess the complementary organisational resources (internal IT capabilities, cross-functional coordination routines, managerial slack) needed to convert blockchain's raw information infrastructure into deployed green innovation capabilities. Second, the effect is strictly increasing in sub-sector pollution intensity: 0.154 in low-pollution sectors, 0.241 in medium-pollution sectors, and 0.346 in high-pollution sectors. This pattern is consistent with a regulatory-pressure interpretation: firms in high-pollution sectors face binding environmental compliance constraints that raise the marginal value of any green innovation capability. Third, the effect is substantially larger in export-intensive firms (0.309) than in firms with low export exposure (0.178), consistent with the view that international buyer pressure on environmental performance amplifies the returns to blockchain-enabled traceability.

Additional robustness checks were conducted using alternative measurement and estimation strategies. Covariance-based SEM (using maximum-likelihood estimation in AMOS 28) produced path estimates within ±0.021 of the PLS-SEM estimates for every hypothesised path, with no change in the pattern of statistical significance. Replacing the five-item GIE scale with a single-item global effectiveness measure produced attenuated but directionally identical findings. Dropping each control variable one at a time altered no substantive conclusion. In the predictive-modelling stage, re-estimating the stacked ensemble with 10-fold cross-validation (rather than 5-fold) produced out-of-sample R^2 and RMSE within ±0.007 of the main estimates. These checks collectively support the robustness of the reported findings.

VI. DISCUSSION

VI.1 Theoretical contributions

The findings contribute to three distinct theoretical conversations. First, they clarify the previously contested empirical record on the relationship between blockchain technology application and green innovation. Prior empirical studies have reported positive, negative, and null direct effects, often within the same broad empirical context. The evidence reported here indicates that the relationship is not a direct one but rather a fully mediated one operating through supply chain integration. Studies that test only the direct path collapse the underlying two-stage transformation — structuring by BTA, bundling by SCI — into a single compound effect whose magnitude depends on the unobserved depth of integration in the sample. The full-mediation pattern documented here reconciles the mixed findings by showing that BTA's association with green innovation operates essentially entirely through inter-organisational integration, meaning that empirical tests that omit the mediator necessarily produce estimates whose magnitude is a confounded function of both pathways (MacKinnon et al., 2007).

Second, the findings advance the resource orchestration perspective by providing a concrete empirical mapping of its three stages — structuring, bundling, and leveraging — onto specific digital and inter-organisational constructs, and by identifying the boundary conditions that govern the effectiveness of each stage. Blockchain's role as the structuring mechanism that converts dispersed supply-chain data into a machine-readable resource pool was theoretically motivated but has lacked prior empirical support of the kind needed to make the resource-orchestration framework operationally usable. Similarly, supply chain integration's role as the bundling mechanism has been hypothesised in conceptual work but not directly tested as a mediator between digital infrastructure and innovation outcomes. The three moderators — trust, task complexity, and green digital learning orientation — further enrich the framework by specifying the organisational and relational conditions that determine the effectiveness of the structuring-to-bundling and bundling-to-leveraging transitions.

Third, and most distinctively, the study contributes to the emerging literature on explainable analytics in management research by demonstrating that gradient-boosting ensembles combined with SHAP-based attribution can (a) validate the theory-driven importance ranking of the focal constructs, (b) identify nonlinear features of their effects that linear-additive structural models cannot detect, and (c) surface interaction patterns whose strength is concentrated in specific regions of the underlying support rather than being constant across it. The saturation pattern in the BTA effect above the mid-range of the scale and the SCI × GDL interaction concentrated at high values of SCI are both substantively meaningful discoveries that would be invisible to the classical approach. This demonstration provides a template for how management researchers can use explainable analytics as a complement to — rather than substitute for — theory-driven empirical work.

VI.2 Managerial and policy implications

The findings carry three clear implications for managers considering blockchain investments and for policy-makers seeking to accelerate green innovation through digital transformation. First, blockchain adoption in isolation is unlikely to deliver measurable sustainability benefits. The technology's contribution flows through its ability to enable deeper integration with supply chain partners, and firms that treat blockchain as an internal IT investment — without simultaneously investing in relational governance and cross-organisational integration processes — are likely to be disappointed by the results. The three moderators provide a diagnostic checklist: before committing significant resources to a blockchain deployment, firms should assess whether their supply chain relationships are sufficiently trust-laden to support shared-ledger deployment, whether their inter-organisational tasks are simple enough to be effectively encoded, and whether their organisational culture is sustainability-oriented enough to translate integrated resources into green innovation outcomes.

Second, the saturation pattern in the BTA effect above the mid-range of the scale carries a specific investment implication: the marginal return on additional blockchain investment declines above a threshold of approximately 'moderate-to-strong' deployment. This finding cautions against maximalist deployment strategies that attempt to blockchain every supply chain transaction and suggests a more selective approach focused on high-impact use cases — end-to-end traceability of regulated materials, cross-firm emissions accounting, and automated environmental compliance — where the marginal benefit of verification remains high.

Third, the heterogeneity results suggest that blockchain-for-sustainability incentive programmes should be preferentially targeted at large firms in high-pollution, export-intensive sectors, where the marginal benefit of intervention is greatest. Small and medium enterprises in low-pollution sectors derive comparatively modest benefits from blockchain adoption and may be better served by simpler digital transformation tools tailored to their specific operational needs. The centrality of supply chain integration in the transformation pathway also suggests that policy efforts should extend beyond subsidising firm-level technology adoption to fostering the cross-firm collaboration networks and relational governance mechanisms that convert digital infrastructure into systemic innovation outcomes. Industry associations, sector consortia, and public-private partnerships are natural vehicles for this broader agenda.

VII. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

This study has developed and applied a multi-factor analytical framework that integrates a theoretically grounded structural equation model with a gradient-boosting ensemble and SHAP-based explainable analytics to examine how blockchain technology application, supply chain integration, and three contextual factors jointly shape green innovation efficiency in Singapore manufacturing. The framework produces three principal findings: supply chain integration fully mediates the BTA–GIE relationship; supply chain trust amplifies and task complexity attenuates the BTA→SCI pathway, while a green digital learning orientation amplifies the SCI→GIE pathway; and a flexible predictive ensemble reveals a saturating nonlinearity in the BTA effect and a concentrated interaction pattern in the SCI × GDL relationship that linear-additive structural models cannot detect.

Three principal limitations suggest directions for future research. First, the cross-sectional research design precludes definitive causal inference; a longitudinal or quasi-experimental study exploiting variation in the timing of blockchain adoption across matched firms would provide stronger evidence on the causal direction of the reported relationships. Second, the analytical sample is confined to Singapore, and while Singapore is a theoretically informative test case, cross-country replication — ideally using identical instruments across several ASEAN economies — would delineate the external validity of the framework. Third, the explainable analytics stage relies on SHAP values computed on a single stacked ensemble; alternative attribution methods (counterfactual explanations, anchors, attention-based attributions for neural models) would provide useful triangulation. Beyond these extensions, promising directions include examining the role of alternative mediators such as absorptive capacity and innovation intermediaries, investigating the interaction between blockchain and adjacent digital technologies (artificial intelligence, Internet of Things, digital twins), and testing the framework in service supply chains where the nature of inter-organisational integration differs substantially from the manufacturing context studied here.

Declarations

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Conflicts of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability: The anonymised survey dataset, trained model artefacts, and analysis scripts supporting the findings of this study are available from the corresponding author upon reasonable request, subject to the participant consent protocol approved by the Singapore Management University Institutional Review Board (protocol reference SMU-IRB-2024-01-037).

Author contributions: T. W. J. led data collection, measurement design and primary writing. P. N. H. X. led the machine-learning implementation, SHAP analysis, and visualisation. M. F. R. led project supervision, funding acquisition, theoretical framing and writing-review and editing. All authors reviewed and approved the final manuscript.

Generative AI statement: The authors declare that no generative AI tools were used in the substantive development of the research propositions, empirical analysis, or interpretation of the findings. Limited use of grammar-checking tools was made in the editing of the manuscript text.

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