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Green supply chain management practices and their implications for organisational sustainability: An empirical investigation using PLS-SEM

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Abstract

Purpose: This study investigates the differential relationships between six green supply chain management (GSCM) practices and three dimensions of organisational sustainability performance economic, environmental, and social grounded in resource-based view (RBV) theory.

Design/Methodology/Approach: A quantitative survey was administered to 267 manufacturing managers. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to examine six GSCM practices green design, green purchasing, green manufacturing, green logistics, reverse logistics, and customer cooperation and their effects on three sustainability performance dimensions.

Findings: GSCM practices exert heterogeneous effects. All six practices significantly predict environmental performance (R^2 = 0.561), with green manufacturing yielding the strongest effect (β = 0.308, $p < .001$). Green design, green purchasing, green manufacturing, and customer cooperation significantly influence economic performance (R^2 = 0.428). Customer cooperation exerts the strongest social performance effect (R^2 = 0.472; β = 0.264, $p < .001$). Environmental performance partially mediates the relationships between green design, green purchasing, and green manufacturing and both economic and social performance.

Practical Implications: Organisations should prioritise GSCM practices strategically in alignment with sustainability objectives. Green manufacturing and green design generate benefits across multiple performance dimensions; customer cooperation is essential for social performance goals.

Originality/Value: This study provides comprehensive empirical evidence of the differential effects of distinct GSCM practices on multidimensional sustainability performance within an RBV framework, offering actionable managerial and policy guidance.

Keywords: Green Supply Chain Management; Sustainability Performance; Triple Bottom Line; Resource-Based View; PLS-SEM; Manufacturing Organizations

1. Introduction

Contemporary organisations face mounting pressure to reconcile economic performance with environmental sustainability and social responsibility. The triple bottom line (TBL) framework, which evaluates performance along economic, environmental, and social dimensions simultaneously, has emerged as a foundational paradigm extending traditional financial metrics (Elkington, 2018). Against this backdrop, green supply chain management (GSCM) has

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evolved from a peripheral concern into a strategic driver that fundamentally reshapes how organisations create and deliver value (Bag et al., 2020).

The global business environment has undergone a significant transformation, with environmental sustainability increasingly recognised as a source of competitive advantage and innovation capability (Sarkis & Zhu, 2018). Organisations implementing GSCM practices report reduced operational costs, enhanced brand equity, stronger stakeholder relations, and improved regulatory compliance (Younis & Sundarakani, 2019). The manufacturing sector has experienced particularly profound change as firms recognise that sustainable production can improve operational effectiveness and reduce environmental impact simultaneously (Bag et al., 2021).

Despite growing scholarly attention, several research gaps remain. First, the differential performance implications of individual GSCM practices across TBL dimensions remain insufficiently understood (Dubey et al., 2019). Second, existing studies have largely focused on specific industries or isolated practices, generating fragmented knowledge (Khan et al., 2020). Third, the mechanisms through which GSCM practices translate into economic, environmental, and social performance require further investigation (Ahmed et al., 2020). Resource-based view (RBV) theory offers a compelling lens: competitive advantage is achieved through the strategic deployment of valuable, rare, inimitable, and non-substitutable (VRIN) resources and capabilities (Barney, 2014), and GSCM practices may be conceptualised as organisational capabilities that enable differentiation and operational efficiency (Wong et al., 2020).

This study bridges these gaps by:

- Developing and empirically validating a comprehensive framework integrating six GSCM practices and examining their heterogeneous effects; and
- Extending RBV theory by conceptualising green supply chain capabilities as VRIN strategic resources that generate differential sustainability performance outcomes.

2. Literature Review and Hypothesis Development

2.1. Theoretical Foundation

RBV theory posits that organisations with VRIN resources achieve superior performance (Barney, 2014). GSCM practices represent a bundle of capabilities integrating environmental considerations throughout the supply chain (Jabbour et al., 2017). These practices require specialised knowledge, technologies, and collaborative relationships that are difficult for competitors to replicate (Feng et al., 2018). The dynamic capabilities extension of RBV emphasises the ability to reconfigure resources in response to changing conditions (Teece, 2018), particularly relevant given evolving environmental regulations and stakeholder demands.

2.2. GSCM Practices

Green Design involves incorporating environmental considerations into product design and development (Sdrolia & Zarotiadis, 2018), including use of less harmful materials, design for recyclability, and packaging waste reduction (Bag et al., 2020).

Green Purchasing incorporates environmental criteria into supplier selection and procurement (Mani et al., 2018), including supplier environmental performance evaluation, environmental certifications, and eco-friendly material prioritisation (Yu et al., 2017).

Green Manufacturing adopts processes minimising environmental impact during production, encompassing cleaner technologies, energy efficiency, waste minimisation, and material recycling (Duarte & Machado, 2017; Kamble et al., 2020).

Green Logistics aims to reduce the environmental impact of transportation, warehousing, and distribution activities through route optimisation, fuel-efficient vehicles, and packaging reduction (Jazairy et al., 2021; Centobelli et al., 2021).

Reverse Logistics encompasses product returns, recycling, remanufacturing, and disposal, closing the supply chain loop and recovering end-of-life product value (Agrawal et al., 2016), supporting circular economy principles (Moktadir et al., 2018).

Customer Cooperation involves engaging customers in environmental initiatives and incorporating their feedback into sustainability activities (Fernando et al., 2019; Green et al., 2012).

2.3. Sustainability Performance

Organisational sustainability performance integrates the TBL across economic (financial wellness, profitability, market share), environmental (carbon emissions, energy use, waste), and social dimensions (employee welfare, community relations, stakeholder engagement; Elkington, 2018; Song et al., 2021; Hussain et al., 2018).

2.4. Hypothesis Development

Drawing on the reviewed literature, 18 hypotheses are proposed (H1a–H6c), each positing a positive relationship between one of six GSCM practices and one of three sustainability performance dimensions. Space constraints preclude full reproduction of all theoretical justifications; representative arguments are provided below for each practice, with the complete conceptual framework displayed in Figure 1.

Green design reduces material and energy costs while differentiating products in the marketplace and reducing lifecycle environmental burdens (Bag et al., 2020; Kumar & Anbanandam, 2020): H1a, H1b, H1c all positive.

Green purchasing extends environmental responsibility upstream, improving supplier quality and reducing supply chain environmental footprints (Mani et al., 2018; Sharma et al., 2021): H2a, H2b, H2c all positive.

Green manufacturing simultaneously reduces operational costs through waste and energy savings and improves working conditions (Bai et al., 2019; Kamble et al., 2020): H3a, H3b, H3c all positive.

Green logistics reduces fuel and distribution costs while lowering emissions (Jazairy, 2020; Zhang et al., 2021): H4a, H4b, H4c all positive.

Reverse logistics recovers material value, reduces waste, and strengthens stakeholder perceptions of responsible management (Agrawal et al., 2016; Kazancoglu et al., 2020): H5a, H5b, H5c all positive.

Customer cooperation enhances loyalty, willingness to pay, and downstream environmental impact (Fernando et al., 2019; Tian et al., 2014): H6a, H6b, H6c all positive.

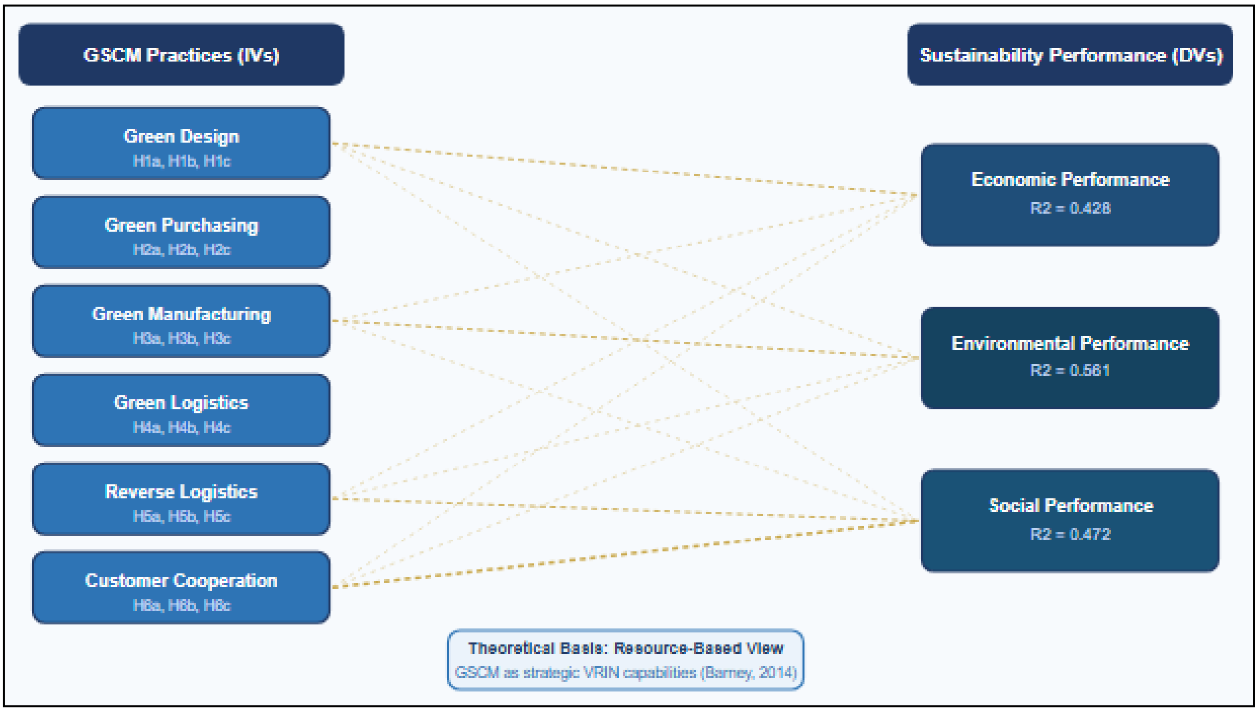


Figure 1 Conceptual Framework: GSCM Practices and Organisational Sustainability Performance (RBV)

3. Research Methodology

3.1. Research Design and Sampling

A quantitative cross-sectional survey design was employed targeting manufacturing organisations across multiple sectors. Purposive sampling targeted supply chain, operations, and sustainability managers with direct GSCM implementation responsibility (Bag et al., 2020). PLS-SEM-based power analysis using G*Power (Faul et al., 2009) identified a minimum sample of 200 (f^2 = 0.15, α = .05, power = 0.80), which the final sample of 267 substantially exceeded.

3.2. Data Collection and Common Method Bias

Data were collected March–August 2024 via structured questionnaires distributed through email and online platforms. A pilot test with 15 academics and practitioners refined item wording. Of 450 questionnaires distributed to 180 organisations, 286 were returned (response rate: 63.56%); 267 were retained after screening. Non-response bias assessment (Armstrong & Overton, 1977) found no significant differences between early and late respondents (all $p > .10$). Common method bias was mitigated through procedural remedies (Podsakoff et al., 2003): anonymity assurance, item order separation, and attention checks. Post-hoc Harman single-factor test yielded 37.42% maximum variance below the 50% threshold (Kock, 2020). Full collinearity VIF values (1.82–3.21) were below the 3.3 threshold (Kock & Lynn, 2012).

3.3. Measurement Instruments

All constructs used validated five-point Likert scales (1 = strongly disagree; 5 = strongly agree) with five items each, adapted from established literature: green design (Zhu et al., 2012; Bag et al., 2020), green purchasing (Mani et al., 2018), green manufacturing (Duarte & Machado, 2017), green logistics (Centobelli et al., 2021; Zhang et al., 2021), reverse logistics (Agrawal et al., 2016), customer cooperation (Fernando et al., 2019; Rehman et al., 2021), economic performance (Geng et al., 2017), environmental performance (Song et al., 2021; Ahmad et al., 2018), and social performance (Hussain et al., 2018; Karaman et al., 2020).

3.4. Analytical Approach

PLS-SEM was implemented in SmartPLS 4.0 (Ringle et al., 2022). PLS-SEM was selected due to its suitability for complex exploratory models with composite constructs, without requiring strict distributional assumptions (Hair et al., 2018). Analysis followed a two-stage procedure: (1) measurement model evaluation and (2) structural model hypothesis testing. Bootstrapping used 5,000 subsamples (Preacher & Hayes, 2008). Predictive relevance was assessed using Stone-Geisser Q^2 (Shmueli et al., 2019). Mediation was tested via indirect effects with bootstrapped confidence intervals. Multi-group analysis used PLS-MGA with permutation-based testing.

4. Results

4.1. Respondent Profile

Table 1 presents respondent and organisational characteristics. Most respondents held managerial positions (68.2%) with a mean experience of 12.6 years. Automotive (18.4%), electronics (16.9%), and chemicals (15.4%) were the most represented sectors. Firm sizes were distributed across small (25.5%), medium (41.9%), and large (32.6%) categories.

Table 1 Respondent and Organisational Profile

Characteristic	Category	Frequency	Percentage
Position	Senior Executive / Director	85	31.8%
	Manager	182	68.2%
Work Experience	Mean: 12.6 years (SD = 8.3)		
Industry Sector	Automotive	49	18.4%
	Electronics	45	16.9%
	Chemicals	41	15.4%

	Textiles	38	14.2%
	Food Processing	35	13.1%
	Consumer Goods	33	12.4%
	Other	26	9.7%
Organisation Size	Small (<100 employees)	68	25.5%
	Medium (100–500)	112	41.9%
	Large (>500)	87	32.6%
Note. N = 267. Response rate = 63.56%. Data collected March–August 2024.			

Note. N = 267.

4.2. Preliminary Analysis

Normality tests confirmed non-normal distributions for several variables, justifying PLS-SEM (Hair et al., 2018). Harman single-factor variance (37.42%) remained below 50%, and VIF values (1.82–3.21) were below 3.3, indicating no critical common method bias or multicollinearity (Kock, 2020; Kock & Lynn, 2012). Missing data (<2%) were handled by mean imputation; seven multivariate outliers were removed. Table 2 presents descriptive statistics and bivariate correlations, all significant at $p < .01$.

Table 2 Descriptive Statistics and Bivariate Correlation Matrix

Variable	M	SD	1	2	3	4	5	6	7-9
1. Green Design	3.67	0.82	1.00						
2. Green Purchasing	3.54	0.79	0.58**	1.00					
3. Green Manufacturing	3.61	0.84	0.61**	0.54**	1.00				
4. Green Logistics	3.48	0.77	0.52**	0.59**	0.49**	1.00			
5. Reverse Logistics	3.42	0.81	0.47**	0.51**	0.53**	0.56**	1.00		
6. Customer Cooperation	3.59	0.85	0.55**	0.48**	0.46**	0.50**	0.44**	1.00	
7. Economic Perf.	3.72	0.76	0.64**	0.52**	0.58**	0.47**	0.43**	0.54**	1.00
8. Environmental Perf.	3.85	0.71	0.67**	0.63**	0.71**	0.58**	0.56**	0.51**	0.59**
9. Social Perf.	3.68	0.78	0.62**	0.57**	0.54**	0.46**	0.50**	0.65**	0.63**
Note. N = 267. **p < .01. All bivariate correlations significant at p < .01.									

Note. N = 267. **p < .01.

4.3. Measurement Model Assessment

Table 3 presents reliability and convergent validity results. All Cronbach's α values (0.842–0.921) and composite reliability values (0.887–0.939) exceeded 0.70 (Hair et al., 2018). All factor loadings exceeded 0.70 (range: 0.742–0.908). AVE values (0.636–0.752) all exceeded 0.50, confirming convergent validity (Fornell & Larcker, 1981).

Table 3 Measurement Model: Reliability and Convergent Validity

Construct (5 items each)	Alpha (α)	Composite Reliability	AVE	Loading Range	√AVE
Green Design (GD)	0.904	0.928	0.721	0.827–0.871	0.849
Green Purchasing (GP)	0.879	0.911	0.672	0.798–0.831	0.820
Green Manufacturing (GM)	0.913	0.935	0.743	0.852–0.877	0.862
Green Logistics (GL)	0.867	0.903	0.652	0.789–0.821	0.807

Reverse Logistics (RL)	0.842	0.887	0.636	0.742–0.826	0.798
Customer Cooperation (CC)	0.893	0.921	0.701	0.821–0.851	0.837
Economic Performance (EcP)	0.901	0.927	0.718	0.824–0.879	0.847
Environmental Performance (EnP)	0.921	0.939	0.752	0.845–0.891	0.867
Social Performance (SoP)	0.907	0.931	0.729	0.844–0.862	0.854
Note. All α > 0.70; CR > 0.70; AVE > 0.50 (Fornell & Larcker, 1981). √AVE = square root of AVE; should exceed inter-construct correlations for discriminant validity.					

Discriminant validity was confirmed using the HTMT criterion (Table 4): all values (0.467–0.782) fell below 0.85 (Henseler et al., 2015), confirming that constructs are empirically distinct.

Table 4 Discriminant Validity: HTMT Ratios

Construct	GD	GP	GM	GL	RL	CC	EcP	EnP
Green Purchasing (GP)	0.612							
Green Manufacturing (GM)	0.647	0.573						
Green Logistics (GL)	0.548	0.623	0.518					
Reverse Logistics (RL)	0.498	0.541	0.562	0.591				
Customer Cooperation (CC)	0.581	0.508	0.487	0.528	0.467			
Economic Performance (EcP)	0.679	0.551	0.614	0.498	0.456	0.571		
Environmental Performance (EnP)	0.709	0.667	0.751	0.613	0.593	0.540	0.626	
Social Performance (SoP)	0.656	0.604	0.573	0.486	0.529	0.687	0.646	0.667
Note. HTMT = heterotrait–monotrait ratio. All values < 0.85, confirming discriminant validity (Henseler et al., 2015).								

Note. All HTMT < 0.85 (Henseler et al., 2015).

4.4. Structural Model and Hypothesis Testing

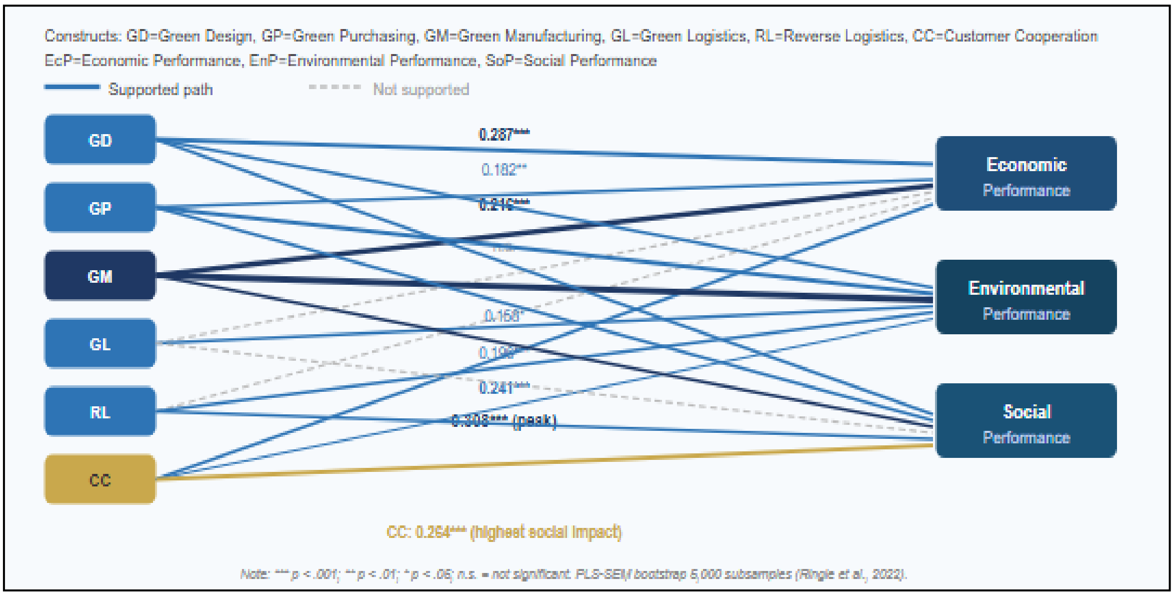
Structural model VIF values (1.67–3.18) confirmed no multicollinearity. Table 5 presents bootstrap hypothesis testing results. For economic performance ($R^2 = 0.428$), green design (β = 0.287, p < .001), green purchasing (β = 0.182, p < .01), green manufacturing (β = 0.216, p < .001), and customer cooperation (β = 0.158, p < .05) were significant, supporting H1a, H2a, H3a, and H6a. Green logistics (β = 0.092, p = .143) and reverse logistics (β = 0.104, p = .114) were not significant (H4a, H5a not supported). For environmental performance ($R^2 = 0.561$), all six practices were significant (H1b–H6b all supported), with green manufacturing yielding the strongest effect (β = 0.308, p < .001). For social performance ($R^2 = 0.472$), five practices were significant: green design, green purchasing, green manufacturing, reverse logistics, and customer cooperation (H1c–H3c, H5c–H6c supported); green logistics was not significant (H4c not supported), with customer cooperation yielding the strongest effect (β = 0.264, p < .001).

Table 5 Hypothesis Testing Results (PLS-SEM Bootstrapping, 5,000 Subsamples)

H	Path	β	t-value	p-value	95% CI	Decision
Economic Performance ($R^2 = 0.428$; $Q^2 = 0.287$)						
H1a	GD → EcP	0.287	4.863	.000***	[0.171, 0.403]	Supported
H2a	GP → EcP	0.182	2.954	.003**	[0.060, 0.304]	Supported
H3a	GM → EcP	0.216	3.741	.000***	[0.102, 0.330]	Supported
H4a	GL → EcP	0.092	1.467	.143	[−0.031, 0.215]	Not supported
H5a	RL → EcP	0.104	1.583	.114	[−0.025, 0.233]	Not supported

H6a	CC → EcP	0.158	2.387	.017*	[0.028, 0.288]	Supported
Environmental Performance (R^2 = 0.561; Q^2 = 0.384)						
H1b	GD → EnP	0.196	3.542	.000***	[0.088, 0.304]	Supported
H2b	GP → EnP	0.241	4.167	.000***	[0.127, 0.355]	Supported
H3b	GM → EnP	0.308	5.429	.000***	[0.196, 0.420]	Supported
H4b	GL → EnP	0.176	2.983	.003**	[0.060, 0.292]	Supported
H5b	RL → EnP	0.189	3.116	.002**	[0.069, 0.309]	Supported
H6b	CC → EnP	0.142	2.284	.022*	[0.020, 0.264]	Supported
Social Performance (R^2 = 0.472; Q^2 = 0.316)						
H1c	GD → SoP	0.223	3.867	.000***	[0.109, 0.337]	Supported
H2c	GP → SoP	0.198	3.341	.001**	[0.082, 0.314]	Supported
H3c	GM → SoP	0.167	2.715	.007**	[0.045, 0.289]	Supported
H4c	GL → SoP	0.087	1.339	.181	[−0.040, 0.214]	Not supported
H5c	RL → SoP	0.153	2.429	.015*	[0.029, 0.277]	Supported
H6c	CC → SoP	0.264	4.512	.000***	[0.148, 0.380]	Supported
Note. β = standardised path coefficient. t-values from bootstrapping (5,000 subsamples). ***p < .001; **p < .01; *p < .05. CI = 95% bias-corrected bootstrap confidence interval.						

Figure 2 Summary of PLS-SEM Path Coefficients   Supported and Non-Supported Hypotheses



Solid arrows = significant; dashed = non-significant. *** p < .001; ** p < .01; * p < .05.

Figure 2 Path coefficient summary

4.5. Effect Sizes and Predictive Relevance

Table 6 presents f^2 and Q^2 results. GSCM practices collectively explained 42.8%, 56.1%, and 47.2% of variance in economic, environmental, and social performance (all > 0.25; Hair et al., 2018). Q^2 values (0.287, 0.384, 0.316) confirmed predictive relevance (Shmueli et al., 2019). Key medium effects: GD → EcP (f^2 = 0.168), GM → EnP (f^2 = 0.187), CC → SoP (f^2 = 0.141).

Table 6 Effect Sizes (f^2) and Model Predictive Relevance

Path	f^2	Effect Size	Managerial Interpretation
Economic Performance (R^2 = 0.428; Q^2 = 0.287)			
GD → EcP	0.168	Medium	Highest economic importance; maintain as strategic priority
GM → EcP	0.094	Small	Efficiency and cost savings via cleaner production
GP → EcP	0.075	Small	Supplier-driven efficiency gains
CC → EcP	0.052	Small	Customer loyalty and revenue effects
Environmental Performance (R^2 = 0.561; Q^2 = 0.384)			
GM → EnP	0.187	Medium	Strongest effect; emission and waste reduction
GP → EnP	0.126	Small-Medium	Upstream environmental responsibility
GD → EnP	0.082	Small	Lifecycle impact reduction through eco-design
RL → EnP	0.073	Small	End-of-life recovery supporting circular economy
GL → EnP	0.067	Small	Transport and distribution emissions reduction
CC → EnP	0.042	Small	Customer-enabled downstream environmental action
Social Performance (R^2 = 0.472; Q^2 = 0.316)			
CC → SoP	0.141	Medium	Highest social impact; stakeholder engagement
GD → SoP	0.104	Small-Medium	Community impact reduction via eco-design
GP → SoP	0.084	Small	Responsible sourcing legitimacy signal
GM → SoP	0.058	Small	Improved worker conditions and workplace safety
RL → SoP	0.047	Small	Responsible end-of-life product management
Note. $f^2 \geq 0.02$ = small; $f^2 \geq 0.15$ = medium; $f^2 \geq 0.35$ = large (Cohen, 1988). $Q^2 > 0$ confirms predictive relevance. All R^2 exceed the 0.25 threshold (Hair et al., 2018).			

Note. $f^2 \geq 0.02$ = small; ≥ 0.15 = medium; ≥ 0.35 = large (Cohen, 1988).

4.6. Importance-Performance Map Analysis (IPMA)

Table 7 Importance-Performance Map Analysis (IPMA)

Practice	Imp. (EcP)	Perf. (EcP)	Imp. (EnP)	Perf. (EnP)	Imp. (SoP)	Perf. (SoP)	Priority
Green Design	0.287	68.4	0.196	68.4	0.223	68.4	High (all dims.)
Green Purchasing	0.182	65.3	0.241	65.3	0.198	65.3	Improve EnP perf.
Green Manufacturing	0.216	61.7	0.308	61.7	0.167	61.7	⚠ Priority gap (EnP)
Green Logistics			0.176				Env. only
Reverse Logistics			0.189		0.153		Env. + Social
Customer Cooperation	0.158	70.1	0.142	70.1	0.264	70.1	✓ Maintain (SoP)
Note. Imp. = importance (β). Perf. = rescaled latent variable score (0–100). = path not significant. GM shows the largest importance-performance gap in environmental performance, indicating the highest improvement priority.							

Table 7 and Figure 4 present IPMA results. Green manufacturing shows the largest importance-performance gap in environmental performance (importance = 0.308; performance = 61.7), indicating a priority investment area. Customer cooperation exhibits high social importance (0.264) and high performance (70.1), suggesting maintenance and leveraging of this already effective capability.

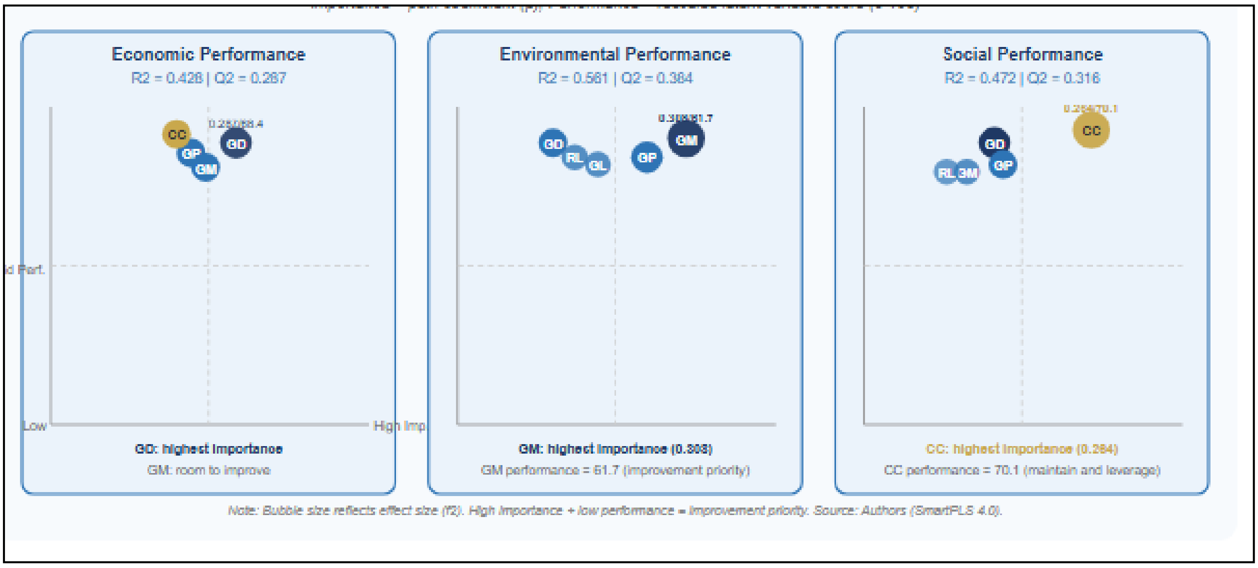


Figure 3 Importance-Performance Map Analysis   Three Performance Dimensions

4.7. Mediation Analysis

Table 8 presents mediation results. Environmental performance partially mediates the GD, GP, and GM relationships with both economic and social performance. All indirect effects are significant with bootstrap CIs excluding zero. The persistence of significant direct effects confirms partial mediation   environmental improvement amplifies but does not wholly explain these GSCM practice effects.

Table 8 Mediation Analysis: Environmental Performance as Mediator

Indirect Path	Indirect Effect (β)	t-value	p-value	95% Bootstrap CI	Mediation Type
Economic Performance as Outcome (Mediator = Environmental Performance)					
GD → EnP → EcP	0.078	2.438	.015*	[0.015, 0.141]	Partial
GP → EnP → EcP	0.096	2.667	.008**	[0.025, 0.167]	Partial
GM → EnP → EcP	0.123	3.000	.003**	[0.042, 0.204]	Partial
Social Performance as Outcome (Mediator = Environmental Performance)					
GD → EnP → SoP	0.069	2.379	.017*	[0.012, 0.126]	Partial
GP → EnP → SoP	0.085	2.576	.010*	[0.020, 0.150]	Partial
GM → EnP → SoP	0.108	2.842	.005**	[0.033, 0.183]	Partial
Note. Bootstrapping 5,000 subsamples. **p < .01; *p < .05. All 95% CIs exclude zero. Partial mediation: direct effects remain significant after inclusion of mediator.					

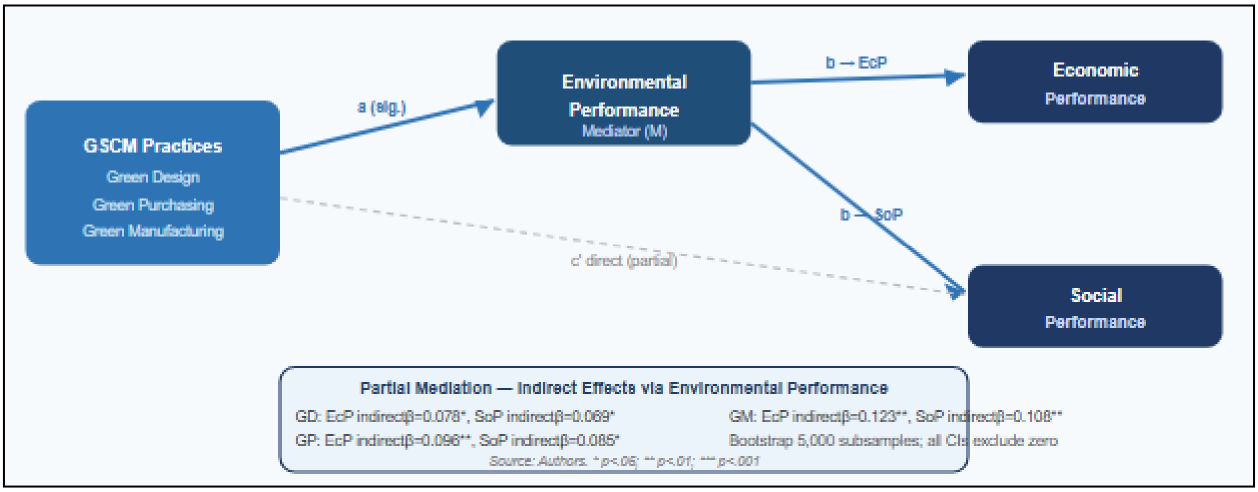


Figure 4 Environmental Performance as Partial Mediator GSCM → Economic/Social Performance

4.8. Multi-Group Analysis

Table 9 presents PLS-MGA results. Larger firms derive significantly stronger economic returns from green design ($\Delta\beta$ = 0.183, p = .042), consistent with scale-based resource leverage. Green manufacturing's environmental impact is significantly stronger in manufacturing-intensive sectors ($\Delta\beta$ = 0.147, p = .031), reflecting the operational scale at which process-level environmental improvements materialise.

Table 9 Multi-Group Analysis (PLS-MGA)

Comparison	Path	Group 1 (β)	Group 2 (β)	Δβ	p-value	Interpretation
Organisation Size	GD → EcP	Small: 0.194	Large: 0.377	0.183	.042*	Larger firms derive stronger economic returns from green design
Industry Intensity	GM → EnP	High-mfg: 0.387	Low-mfg: 0.240	0.147	.031*	GM impact on EnP stronger in manufacturing-intensive sectors
Note. PLS-MGA permutation test. *p < .05. Δβ = absolute difference in path coefficients. High-mfg = automotive, electronics, chemicals; Low-mfg = food, consumer goods, textiles.						

Note. *p < .05.

5. Discussion

5.1. Findings and Theoretical Implications

This study provides significant empirical evidence of the differential relationships between six GSCM practices and three TBL dimensions. The consistent strong impact of all six practices on environmental performance confirms that comprehensive GSCM implementation aligns well with environmental objectives (Ahmad et al., 2018) and that GSCM practices collectively constitute VRIN capabilities for environmental competitive advantage (Barney, 2014). The explained variance of 56.1% in environmental performance underscores the primacy of GSCM as a driver of environmental sustainability in manufacturing.

The selective relationships observed for economic and social performance introduce important boundary conditions. Green design's strong economic effect (f^2 = 0.168, medium) advances RBV theory by demonstrating that eco-design capabilities generate direct economic returns through differentiation and cost reduction (Wong et al., 2020). The robust pan-dimensional effects of green manufacturing confirm its status as the most versatile sustainability capability. Customer cooperation's strong social impact (f^2 = 0.141) extends stakeholder theory, demonstrating that collaborative engagement reinforces legitimacy and stakeholder relationships (Fernando et al., 2019).

The non-significant short-run economic effects of green logistics and reverse logistics are consistent with the temporal investment lag hypothesis infrastructure-intensive environmental investments materialise over multi-year horizons (Kazancoglu et al., 2020). The partial mediation of environmental performance confirms the win-win hypothesis: environmental improvements serve as amplifying mechanisms for economic and social sustainability benefits (Geng et al., 2017).

5.2. Practical Implications

Organisations should prioritise GSCM practices in alignment with their primary sustainability objectives. For environmental performance, comprehensive implementation of all six practices is recommended, with particular emphasis on green manufacturing where the importance-performance gap is largest. For economic returns, green design, green purchasing, and green manufacturing offer the most reliable benefits. For social performance, customer cooperation is the pre-eminent lever. Portfolio adoption implementing multiple complementary practices generates synergies that address multiple sustainability dimensions simultaneously. Multi-group findings indicate that implementation strategies should be calibrated to organisational size and industry context.

5.3. Limitations and Future Research

Key limitations include: the cross-sectional design limits causal inference; self-reported measures introduce potential social desirability bias; the manufacturing-only sample constrains generalisation; and the study addresses only six practices. Future research should employ longitudinal designs (Ahmed et al., 2020), investigate additional mediating and moderating mechanisms (Belhadi et al., 2019), conduct cross-cultural comparative studies (Dubey et al., 2019), and examine GSCM practice bundles and configurational synergies (Bag et al., 2021).

6. Conclusion

This study examined the heterogeneous relationships between six GSCM practices and three sustainability performance dimensions in 267 manufacturing organisations. All six practices significantly predict environmental performance, with green manufacturing generating the strongest impact ($\beta = 0.308$). Green design, green purchasing, green manufacturing, and customer cooperation predict economic performance; customer cooperation generates the strongest social performance effect ($\beta = 0.264$). Environmental performance partially mediates three key GSCM practice effects on economic and social performance. These findings confirm that GSCM practices function as strategic VRIN capabilities, advance RBV theory in the sustainability context, and provide evidence-based prioritisation guidance for managers and policymakers. As environmental pressures intensify and stakeholder demands evolve, robust GSCM capabilities will be increasingly vital to organisational legitimacy, resilience, and long-term sustainable performance.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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