

Effect of Reverse Logistics Efficiency on Supply Chain Performance of Manufacturing Companies in Southwest Nigeria

Aworemi, J. R.¹; Ayantoyinbo, B. B.^{2*}; Akintola, A. K.^{3*}

^{1,2,3*}Department of Transport Management, Faculty of Management Sciences, Ladoké Akintola University of Technology, P. M. B. 4000, Ogbomosho. Oyo State, Nigeria.

*Corresponding author: akakintola@lautech.edu.ng

Abstract— The practice of reverse logistics allows manufacturing firms to capture value from returned goods, parts, packages, and materials. However, unpredictable timing, condition, and destination could present cost and inventory management challenges. This study sought to investigate the influence of the efficiency of reverse logistics on the supply chain performance of selected manufacturing firms in Southwest Nigeria. A cross-sectional survey collected 395 valid questionnaires from ten listed firms. The variables for analysis were cycle-time reduction, customer satisfaction with the return process, asset recovery, sustainability impact, technology adoption, and returned-inventory management. The study result revealed that reverse logistics efficiency significantly influenced supply chain performance, with technology adoption making the strongest contribution ($B = 0.495$), followed by returned-inventory management ($B = 0.288$) and cycle-time reduction ($B = 0.270$). The regression model was statistically significant ($F = 106.559$, $p < 0.001$) and explained 71.4% of the variation in supply chain performance ($R^2 = 0.714$). The study establishes reverse logistics as an important operational competence of manufacturing organizations, not a mere disposal process. It recommends an integrated approach to return authorization, tracking, disposition, collaboration, and performance metrics in all dimensions.

Keywords— Reverse logistics, circular economy, technology adoption, asset recovery, returned inventory, supply chain performance.

I. INTRODUCTION

Reverse logistics has become a central supply chain capability because circular manufacturing depends on moving products and materials from users back to inspection, repair, reuse, remanufacturing, recycling, or responsible disposal points (Mishra et al., 2023; Govindan and Hasanagic, 2018). Unlike forward distribution, return flows are uncertain in volume, timing, condition, location, and residual value. These uncertainties create handling cost, delayed customer resolution, inventory congestion, and loss of recoverable value. Consequently, reverse logistics efficiency should be assessed as an integrated system rather than as a warehouse or customer-service activity. Meanwhile, manufacturers in resource-constrained economies have strong reasons to recover materials because imported inputs, foreign-exchange pressure, waste-disposal cost, and regulatory expectations increase the value of reuse and recycling. However, weak collection networks, fragmented information, inconsistent quality, and limited recovery infrastructure can make returns expensive. The profitability of reverse systems therefore varies across firms and products, which means that circular intent does not automatically improve performance (Bressanelli et al., 2019; Rajabzadeh et al., 2024).

Furthermore, cycle time, customer satisfaction, asset recovery, sustainability, technology, and returned-inventory control capture different aspects of efficiency. Faster processing protects customer relationships and reduces storage time, while asset recovery determines how much economic and material value is retained. Technology improves identification and visibility, and inventory management prevents returned goods from becoming unclassified stock. These dimensions are connected; for instance, tracking can shorten cycle time, but

speed without accurate condition assessment may direct recoverable items to disposal. Moreover, digital technologies are increasingly important because reverse networks require information across customers, distributors, transport providers, warehouses, repair centres, recyclers, and manufacturers. The smart circular economy framework explains how data capture, integration, and analytics support circular strategies (Kristoffersen et al., 2020). Yet technology creates value only when processes and partner responsibilities are redesigned. A blockchain or Internet of Things application cannot compensate for unclear return policies, inconsistent product codes, or absent recovery markets.

Accordingly, this study examines the effect of reverse logistics efficiency on supply chain performance among manufacturing companies in Southwest Nigeria. It estimates the joint explanatory power of the reverse logistics dimensions and compares their unique contributions. The paper also interprets the results through the Natural Resource-Based View, which regards pollution prevention and product stewardship capabilities as possible sources of operational and competitive value (Hart, 1995).

II. LITERATURE REVIEW

A. Reverse Logistics Efficiency and Circular Supply Chains

Reverse logistics covers the planned movement and management of products, packaging, components, and materials from downstream locations toward points where value can be recovered or environmental harm can be controlled. It includes return authorisation, collection, transportation, inspection, sorting, disposition, repair, remanufacturing, recycling, resale, and disposal (Rogers and Tibben-Lembke, 2001; Mishra et al., 2023). Efficiency

therefore means more than rapid transport. It concerns the ability to select the highest-value feasible recovery option while controlling cost, service delay, inventory, and environmental impact. Return uncertainty is the central operational challenge. Forward supply chains usually move standard products toward known customers, whereas reverse systems receive items of uncertain quality and residual value. Circular supply chain redesign studies identify product condition, return quantity, timing, and partner coordination as major barriers (Bressanelli et al., 2019). Consequently, firms require flexible capacity and clear disposition rules. Products that can be resold should not follow the same path as items needing repair, material recovery, or safe disposal.

Moreover, cycle-time reduction is important because delay destroys value. Returned products may become obsolete, deteriorate, occupy warehouse capacity, or frustrate customers while waiting for inspection and decision. However, a narrow speed target can produce premature disposal. Efficient cycle time should therefore measure the interval from return request to final disposition while retaining decision quality. Process mapping, pre-authorisation, standard reason codes, inspection criteria, and decentralised decision rights can reduce delay without sacrificing recovery value (Blackburn et al., 2004). On the other hand, Customer satisfaction connects reverse logistics with market performance. After a product fails, trust can be preserved with a clear return policy, easy pickup, clear status updates, and prompt refunds or replacements. However, excessively generous returns may result in higher expenses, fraud, and needless transportation. Firms therefore need differentiated policies based on product value, defect type, warranty, customer segment, and recovery opportunity. The circular economy perspective adds that customer communication can also support take-back and responsible disposal, extending the relationship beyond complaint resolution (Mishra et al., 2023).

Furthermore, asset recovery concerns the proportion of returned value retained through reuse, repair, refurbishment, remanufacturing, parts harvesting, and recycling. Product design influences this outcome because modularity, durability, disassembly, and material identification determine whether recovery is technically and economically feasible (Bocken et al., 2016). Therefore, reverse logistics efficiency cannot be improved entirely downstream. Return data should influence design, sourcing, packaging, and supplier development so that future products enter higher-value recovery loops. Sustainability impact requires attention to the net environmental result. Collection and processing create transport, energy, and material use, which means that recovery is not automatically beneficial. Firms should compare avoided virgin material, landfill reduction, emissions, and energy use with the impact of the recovery process. Circular economy research therefore promotes value retention but also warns that poor network design can shift rather than reduce environmental burden (Govindan and Hasanagic, 2018; Rajabzadeh et al., 2024).

However, technology adoption supports visibility and decision speed. Radio-frequency identification, barcodes, Internet of Things sensors, enterprise systems, analytics, digital

product passports, and blockchain can record product identity, ownership, condition, location, and recovery history. The smart circular economy framework shows that digital capability can connect circular strategy with operational decisions (Kristoffersen et al., 2020). Recent reverse logistics architecture research also emphasises integrated data and decision processes across organisational levels (Sun et al., 2024). However, technology investment should follow process design and data governance rather than precede them. Returned-inventory management is distinct from forward inventory control because items have different conditions and destinations. Without accurate classification, firms may overstate saleable stock, lose high-value components, or store obsolete goods. Systems should therefore separate items for immediate resale, repair, refurbishment, parts recovery, recycling, and disposal, while recording age and expected recovery value. This classification allows managers to prioritise action and link physical inventory with financial and environmental outcomes (Bressanelli et al., 2019; Kristoffersen et al., 2020).

The Natural Resource-Based View explains how reverse logistics can support performance. Product stewardship and pollution-prevention capabilities reduce material loss and environmental exposure while creating knowledge that competitors may find difficult to reproduce (Hart, 1995). Nevertheless, collection assets or software alone are not rare resources. Advantage emerges from integrated routines, partner relationships, recovery knowledge, product data, and continuous learning. Reverse logistics becomes strategic when these capabilities improve forward design and supply decisions as well as manage returns.

Empirical and case evidence generally supports the performance value of reverse logistics, but outcomes depend on context. Mishra et al. (2023) showed that reverse logistics enables circular-economy objectives, while Sun et al. (2024) demonstrated the importance of technology-aware network design. Rajabzadeh et al. (2024) further showed that reverse-channel sourcing involves cost and resilience trade-offs. Therefore, a strong positive average effect may coexist with weaker performance in firms that lack return volume, product recoverability, digital capability, or reliable partners. A gap remains in developing-country manufacturing evidence. Research often examines optimisation models, high-technology products, or retail case studies, while fewer studies estimate the relative contribution of cycle time, customer satisfaction, asset recovery, sustainability, technology, and inventory management within one African manufacturing model (Mishra et al., 2023; Sun et al., 2024). This paper addresses the gap and identifies the capabilities with the strongest association with supply chain performance.

B. Conceptual Framework

The framework treats reverse logistics efficiency as a multidimensional capability. Cycle-time reduction and customer satisfaction represent responsiveness, asset recovery and sustainability impact represent circular value, while technology adoption and returned-inventory management provide information and control. These dimensions are expected to influence supply chain performance jointly,

although their coefficients may differ because each addresses a different source of return-flow uncertainty (Kristoffersen et al., 2020; Sun et al., 2024).

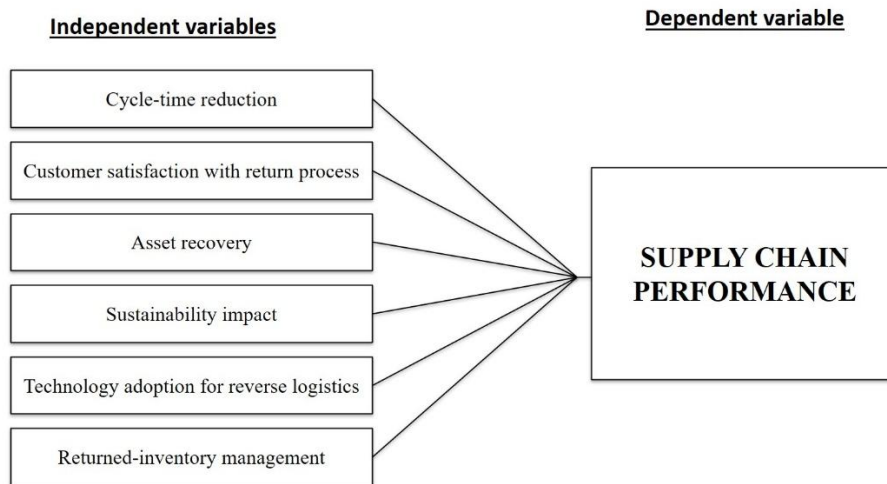


Figure 1. Conceptual framework for the Study

Source: Author's conceptualization (2026)

TABLE 1. Sample-size distribution by manufacturing company

S/N	Company	Staff strength	Staff share	Proportion of 145	Minimum allocation plus proportion	Sample
1	Cadbury Nigeria Plc	356	0.94%	1.37	25 + 1 = 26	26
2	Unilever Nigeria Plc	498	1.32%	1.92	25 + 2 = 27	27
3	Dangote Cement Plc	21,418	56.82%	82.39	25 + 82 = 107	107
4	Lafarge Africa Plc	1,478	3.92%	5.69	25 + 6 = 31	31
5	Okomu Oil Palm Plc	280	0.74%	1.08	25 + 1 = 26	26
6	Presco Plc	9,000	23.88%	34.62	25 + 35 = 60	60
7	May and Baker Nigeria Plc	411	1.09%	1.58	25 + 2 = 27	27
8	Neimeth International Pharmaceuticals Plc	250	0.66%	0.96	25 + 1 = 26	26
9	Beta Glass Plc	1,400	3.71%	5.39	25 + 5 = 30	30
10	Nestle Nigeria Plc	2,603	6.9%	10.01	25 + 10 = 35	35
	Total	37,694	100%	145		395

Source: Researcher's compilation, 2025.

III. METHODOLOGY

The study used a cross-sectional survey of ten listed manufacturing companies in Southwest Nigeria. The firms represented consumer goods, industrial goods, agriculture, health and pharmaceutical, and conglomerate sectors and had reported sustainable transport or circular-economy practices. From a target population of 37,694 employees, Taro Yamane's finite-population procedure produced a sample of 395 at a 5% error level. Multistage sampling combined purposive firm selection, sectoral quota allocation, and disproportionate stratified random sampling. Respondents were drawn from logistics, procurement, transport, production, warehousing, and sales functions. A structured five-point Likert questionnaire measured cycle-time reduction, customer satisfaction with the return process, asset recovery, sustainability impact, technology adoption for reverse logistics, returned-inventory management, and supply chain performance. The reverse logistics scale recorded a Cronbach's alpha of 0.846, while the

overall instrument recorded 0.818. The joint and independent effects of the reverse logistics dimensions were estimated using multiple regression. Model evaluation used R, R Square, adjusted R Square, standard error, ANOVA, unstandardised and standardised coefficients, t statistics, significance values, tolerance, Variance Inflation Factor, and likelihood-ratio model fitting. Statistical decisions were made at the 0.05 level. Composite mean scores represented each construct, responses were analysed anonymously, and participation was voluntary.

$$SCP_i = \beta_0 + \beta_1 CTR_i + \beta_2 CSR_i + \beta_3 AR_i + \beta_4 SI_i + \beta_5 TARL_i + \beta_6 RIM_i + \varepsilon_i \quad (1)$$

where SCP is supply chain performance, CTR is cycle-time reduction, CSR is customer satisfaction with the return process, AR is asset recovery, SI is sustainability impact, TARL is technology adoption for reverse logistics, RIM is returned-inventory management, beta values are coefficients, and epsilon is the error term.

IV. RESULTS

A. Socio-economic Characteristics

The sample represented mature and relatively large manufacturing operations. Consumer goods accounted for the largest sectoral share, 41.8% of respondents worked in companies operating for 11-20 years, and 48.4% worked in firms with 251-1000 employees. The dominant turnover category was 501 million to 5 billion naira, while 57.2% of respondents had occupied their current positions for at least four years. The profile supports informed assessment of return handling, inventory, technology, and supply chain practices.

TABLE 2. Socio-economic characteristics of respondents

Profile indicator	Dominant category	Frequency	Percent
Sector with largest representation	Consumer goods	155	39.2
Most common company age	11-20 years	165	41.8
Most common workforce size	251-1000 employees	191	48.4
Most common annual turnover	501 million - 5 billion naira	223	56.5
Largest respondent designation	Sales officer	97	24.6
Most common tenure in current role	4-6 years	139	35.2

Source: Researcher's Survey, 2025.

B. Effect of Reverse Logistics Efficiency on Supply Chain Performance

This section ascertains the effect of reverse logistics efficiency on supply chain performance, where supply chain performance is modelled as a function of cycle time reduction (CTR), customer satisfaction with return process (CSR), Asset Recovery (AR), Sustainability Impact, Technology adoption to manage reverse logistics (TARL) and Track and Manage returned Inventory. Therefore, the results (Table 4.5-4.7) are interpreted through the model summary, ANOVA and coefficients to explain strength overall model significance and contribution of each independent variable of reverse logistics efficiency to supply chain performance.

The result of this findings in Table 3 indicates a very strong effect of reverse logistics efficiency and supply chain performance, because the multiple correlation coefficient is high ($R = 0.845$) indicating a very strong positive effect of reverse logistics efficiency on supply chain performance. According to Cohen (1988), an R value above 0.80 represents a very strong effect, suggesting that improvements in reverse logistics efficiency are closely affect improvements in supply chain performance.

TABLE 3. Model summary of regression analysis on reverse logistics efficiency

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.845a	.714	.707	.5190

a. Predictors: (Constant), cycle time reduction, customer satisfaction, asset recovery, sustainability impact, technology adoption to manage reverse logistics and inventory management. Dependent variable: supply chain performance.

Source: Researcher's Analysis, 2025.

TABLE 4. ANOVA for the reverse logistics efficiency regression model

Model	Source	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	258.287	9	28.699	106.559	.000b
	Residual	103.688	385	.269		
	Total	361.975	394			

Dependent variable: supply chain performance. Predictors: (Constant), cycle time reduction, customer satisfaction, returned product recycle, refurbish, reuse (asset recovery), sustainability impact, technology use to manage reverse logistics and inventory management.

Source: Researcher's Analysis, 2025.

The regression model in Table 4 show that all the reverse logistics efficiency measures have positive and statistically significant effects on supply chain performance at the 0.05 level. Also, in table 5 Each predictor has a significance value of 0.000 ($p < 0.001$), indicating that the reverse logistics efficiency variables significantly contribute to supply chain performance. The largest standardized beta coefficient is 0.495, representing the use of technology to manage reverse logistics. This means that the use of technology, especially block chain technology makes the strongest unique contribution to explaining the dependent variable (supply chain performance) when the variance explained by all other variables in the model is controlled for.

In table 6, regarding multi-collinearity diagnostics, the Variance Inflation Factor (VIF) values are greater than 1.0, indicating that multi-collinearity is not a concern. The largest standardized beta coefficient (ignoring the sign) represents the variable that makes the strongest unique contribution to explaining the dependent variable. Tolerance and VIF are commonly used cut-off criteria for determining the presence of multi-collinearity (i.e., high correlation among independent variables). A tolerance value less than 0.10 or a VIF value greater than 10 indicates potential multi-collinearity problems. The tolerance values for the independent variables are 0.3, 0.4, 0.4, 0.7, 0.6, 0.3, 0.3, 0.5, and 0.4, all of which are greater than 0.10. Therefore, the model does not violate the multi-collinearity assumption. This is further supported by the VIF values of 2.598, 2.466, 2.374, 1.324, 1.473, 2.959, 3.107, 1.785, and 2.310, which are well below the cut-off point of 10.

Taken together, the relative magnitudes of the standardized beta coefficients show that the use of technology to manage reverse logistics ($\beta = 0.495$) exerts the strongest effect on supply chain performance, followed by tracking and managing returned inventory ($\beta = 0.288$), cycle time reduction ($\beta = 0.270$), asset recovery ($\beta = 0.129$), and customer satisfaction ($\beta = 0.104$). The findings of this study indicate that reverse logistics efficiency strongly enhances supply chain performance, primarily driven by digital technology adoption. The prominence of technology (e.g., block chain and IoT) aligns with recent findings that digitalization closes the loop in circular supply chains by enhancing traceability and recovery rates (Kazancoglu et al., 2021). The negative coefficient for supplier collaboration indicates that, in contexts with low technological integration, increased collaboration without digital transparency may lead to coordination inefficiencies. This caveat was noted by Garza-Reyes et al. (2020) in developing economies. This finding underscores the Natural

Resource-Based View (NRBV), which posits that competitive advantage stems from rare and inimitable capabilities such as technology-integrated return systems rather than partnerships alone (Wong et al., 2020).

TABLE 5. Regression coefficients for reverse logistics efficiency

Predictor	B	Std. Error	Beta	t	Sig.
Constant	.339	.323		1.047	.000
Percentage of product returned by customers	.031	.037	.037	8.420	.000
Cycle time reduction	.020	.046	.270	4.360	.000
Budget allocated to manage returns	.019	.046	.018	4.240	.002
Customer satisfaction with return process	.477	.143	.104	3.329	.001
Asset recovery	.194	.050	.129	3.887	.000
Inventory management	.714	.116	.288	6.135	.000
Sustainability impact	.243	.092	.127	2.632	.000
Technology adoption	.731	.054	.495	13.570	.000
Collaboration with suppliers in managing returns	.099	.044	-.093	-2.234	.002
Supply chain performance	.767	.234	.315	13.321	.000

Source: Researcher's Analysis, 2025.

Table 6 presents the Model Fitting Information. Since the p-value is less than 0.05 ($p = 0.0001$), the regression model that includes the independent variables (final model) provides a significantly better fit than the null model with no predictors. This indicates that the inclusion of reverse logistics efficiency variables significantly improves the model's explanatory power. The result implies that the model fits the data adequately and that the estimated effects of reverse logistics efficiency are consistent with the observed supply chain performance reported by the respondents. Therefore, there is sufficient statistical evidence to support the appropriateness of the model for interpreting the effect of reverse logistics efficiency on supply chain performance in this study.

TABLE 6. Model fitting information for reverse logistics efficiency

Model	-2 Log Likelihood	Chi-Square	df	p-value
Null	368.492			
Final	167.434	201.058	6	0.0001

Source: Researcher's Analysis, 2025.

TABLE 7. Parameter estimates for reverse logistics efficiency

Type	Category	Estimate	Wald	df	p-value
Dependent variable	[D33=1]	4.357	70.650	1	0.0001
	[D33=2]	2.458	28.501	1	0.0001
	[D33=3]	1.450	10.684	1	0.001
Independent variable	[D25=1]	4.046	16.050	1	0.0001
	[D25=2]	1.276	8.296	1	0.004
	[D25=3]	4.639	76.927	1	0.0001
	[D28=1]	1.659	1.238	1	0.266
	[D28=2]	3.565	15.832	1	0.0001
	[D28=3]	1.418	28.310	1	0.0001

Source: Researcher's Analysis, 2025.

The parameter estimates of the model fitted to examine the effect of reverse logistics efficiency on supply chain performance are presented in Table 7. The results indicate that all the independent variables measuring reverse logistics

efficiency has statistically significant effects on supply chain performance, as their p-values are less than 0.05.

V. DISCUSSION

The model recorded $R = 0.845$ and $R\text{ Square} = 0.714$, indicating that the reverse logistics dimensions explain a substantial proportion of supply chain performance. This magnitude supports the view that returns management is a core operating system rather than a peripheral environmental activity. Reverse logistics determines how quickly firms resolve customer problems, recover material and financial value, control uncertain stock, and learn from product failure. The result is consistent with circular supply chain research that places reverse flows at the centre of value retention (Mishra et al., 2023; Govindan and Hasanagic, 2018). The adjusted $R\text{ Square}$ of 0.707 remains close to the unadjusted value, indicating stable explanatory power after accounting for the number of predictors. In practical terms, the dimensions are not merely adding statistical complexity; together they capture important features of return performance. However, 28.6% of variation remains outside the model. Product design, return volume, partner capability, recovery market prices, transport infrastructure, and management support may account for part of this unexplained share (Bressanelli et al., 2019; Rajabzadeh et al., 2024). The significant ANOVA result confirms that the variables jointly provide a reliable explanation of supply chain performance. This joint effect is theoretically reasonable because reverse logistics outcomes depend on coordinated processes. Faster cycle time without inventory visibility can move errors more quickly, while technology without recovery options can generate data without value. Therefore, firms should design one end-to-end return process connecting customer service, transport, inspection, inventory, finance, sustainability, and recovery partners. The systems should share definitions and decision rules so that each return receives a timely and economically justified disposition.

Furthermore, technology adoption made the strongest unique contribution with $\beta = 0.495$. This finding confirms the importance of digital visibility in uncertain return flows. Identification, return authorisation, location tracking, condition records, and recovery history allow firms to reduce search time and make faster disposition decisions. The smart circular economy framework similarly argues that digital technologies connect data with circular strategy (Kristoffersen et al., 2020), while recent architecture research shows that integrated decision support can improve reverse logistics design (Sun et al., 2024). Nevertheless, technology should be governed by common product codes, data standards, access rights, and partner participation. Returned-inventory management produced the second largest contribution at $\beta = 0.288$. This result shows that recoverable value can be lost after products arrive at the facility if they are not classified and prioritised. Returned items should be separated by condition, ownership, warranty, expected recovery value, and required action. Ageing reports should identify products waiting for inspection, repair, resale, recycling, or disposal. Moreover, financial records should distinguish saleable inventory from uncertain return

stock so that managers do not overstate availability or hide working capital.

Furthermore, Cycle-time reduction followed with $\beta = 0.270$. Faster processing improves customer resolution, releases warehouse space, and reduces deterioration or obsolescence. However, the objective should be decision speed rather than physical movement alone. Blackburn et al. (2004) showed that the time value of returned products differs across categories, implying that firms should prioritise high-value and time-sensitive returns. Standard return codes, pre-authorisation, digital documents, and clear decision thresholds can shorten the cycle while preserving recovery quality. Asset recovery and sustainability impact recorded positive but smaller coefficients. Their lower magnitude does not make them unimportant. Recovery depends on product design, condition, market demand, and processing capacity, while environmental benefit depends on whether recovered materials genuinely replace virgin inputs. Bocken et al. (2016) show that design for durability, disassembly, and reuse influences circular value. Therefore, manufacturers should use return data to improve product design, packaging, component standardisation, and supplier specifications rather than limit reverse logistics to downstream handling.

Moreover, customer satisfaction also contributed positively. The coefficient indicates that returns are part of the customer experience and can protect loyalty when the process is clear and timely. Nevertheless, customer convenience must be balanced with fraud prevention, transport cost, and recovery value. A differentiated policy can provide rapid replacement for low-risk cases while requiring inspection for high-value or uncertain returns. Status visibility and communication are especially important because customers often evaluate fairness through the clarity and predictability of the process rather than speed alone. The negative coefficient for supplier collaboration requires careful interpretation. Collaboration can increase meetings, handoffs, and data inconsistency when partners lack digital transparency or clear decision rights. This does not mean collaboration is inherently harmful. Rather, it suggests that relationships should be supported by shared product codes, service-level agreements, responsibility matrices, data access, and recovery targets. Rajabzadeh et al. (2024) show that reverse channels involve risk and resilience trade-offs, while Sun et al. (2024) emphasise integrated decision architecture. Thus, structured collaboration is more valuable than informal coordination. The model-fitting results provide further support because the final model reduced -2 Log Likelihood from 368.492 to 167.434 and recorded chi-square of 201.058 with $p = 0.0001$. The parameter estimates were significant for most categories, although one category recorded $p = 0.266$. This variation reinforces the need to avoid treating every category or operational condition as equally influential. Managers should use product and return segmentation to identify where technology, speed, recovery, or customer service has the greatest effect.

However, the findings support the Natural Resource-Based View because technology-integrated return systems reduce waste and create operational knowledge (Hart, 1995). Yet the advantage does not arise from software or equipment alone. It

comes from routines that connect customer information, inventory, recovery partners, product design, and environmental measurement. Such routines are harder to imitate because they develop through experience and cross-functional learning. Therefore, firms should treat reverse logistics as a capability-development programme and not as a short-term waste initiative. Overall, the results show a clear order of managerial priority: establish digital visibility, control returned inventory, shorten decision time, strengthen recovery, and protect customer and environmental value. These priorities should not be implemented separately. A return dashboard should combine cycle time, recovery rate, inventory age, customer resolution, financial value retained, emissions, and disposal share. Balanced measurement will prevent a narrow improvement in speed or cost from weakening circular outcomes (Kristoffersen et al., 2020; Mishra et al., 2023).

VI. CONCLUSION AND RECOMMENDATIONS

The paper concludes that reverse logistics efficiency has a strong and statistically significant effect on supply chain performance. The model explains 71.4% of the variation in performance, while technology adoption, returned-inventory management, and cycle-time reduction make the largest contributions. Asset recovery, sustainability impact, and customer satisfaction also contribute positively. The findings establish that effective returns management creates operational, financial, customer, and environmental value when processes are integrated.

Manufacturing firms should implement one digital return platform covering authorisation, tracking, inspection, inventory classification, disposition, and recovery history. Returned items should be segmented by condition and value, with time limits for each decision stage. Firms should establish repair, refurbishment, recycling, and parts-recovery partnerships supported by service-level agreements and shared data standards. Performance dashboards should combine cycle time, recovery rate, inventory ageing, customer resolution, value retained, emissions, and disposal. Future studies should use longitudinal records, include product-design variables, and compare industries with different return volumes and recovery opportunities.

REFERENCES

- [1]. Abbasi, B., & Abareshi, A. (2024). Impacts of institutional pressures and internal abilities on green performance of transport and logistics companies. *International Journal of Logistics Management*, 35(6), 2087-2113. <https://doi.org/10.1108/IJLM-09-2023-0382>
- [2]. Al Karim, R., Kabir, M. R., Rabiul, M. K., Kawser, S., & Salam, A. (2024). Linking green supply chain management practices and environmental performance in the manufacturing industry: A hybrid SEM-ANN approach. *Environmental Science and Pollution Research*, 31(9), 13925-13940. <https://doi.org/10.1007/s11356-024-32098-3>
- [3]. Banister, D. (2008). The sustainable mobility paradigm. *Transport Policy*, 15(2), 73-80. <https://doi.org/10.1016/j.tranpol.2007.10.005>
- [4]. Blackburn, J. D., Guide, V. D. R., Souza, G. C., & Van Wassenhove, L. N. (2004). Reverse supply chains for commercial returns. *California Management Review*, 46(2), 6-22. <https://doi.org/10.2307/41166207>
- [5]. Bocken, N. M. P., de Pauw, I., Bakker, C., & van der Grinten, B. (2016). Product design and business model strategies for a circular economy. *Journal of Industrial and Production Engineering*, 33(5), 308-320. <https://doi.org/10.1080/21681015.2016.1172124>

- [6]. Bressanelli, G., Perona, M., & Saccani, N. (2019). Challenges in supply chain redesign for the circular economy: A literature review and a multiple case study. *International Journal of Production Research*, 57(23), 7395-7422. <https://doi.org/10.1080/00207543.2018.1542176>
- [7]. Carter, C. R., & Rogers, D. S. (2008). A framework of sustainable supply chain management: Moving toward new theory. *International Journal of Physical Distribution and Logistics Management*, 38(5), 360-387. <https://doi.org/10.1108/09600030810882816>
- [8]. Epoh, L. R., & Mafini, C. (2024). A model for green supply chain management in the South African manufacturing sector. *Cogent Business & Management*, 11(1), 2390213. <https://doi.org/10.1080/23311975.2024.2390213>
- [9]. Govindan, K., & Hasanagic, M. (2018). A systematic review on drivers, barriers, and practices towards circular economy: A supply chain perspective. *International Journal of Production Research*, 56(1-2), 278-311. <https://doi.org/10.1080/00207543.2017.1402141>
- [10]. Hart, S. L. (1995). A natural-resource-based view of the firm. *Academy of Management Review*, 20(4), 986-1014. <https://doi.org/10.5465/amr.1995.9512280033>
- [11]. International Organization for Standardization. (2015). *ISO 14001:2015 environmental management systems - Requirements with guidance for use*. ISO.
- [12]. International Organization for Standardization. (2018a). *ISO 45001:2018 occupational health and safety management systems - Requirements with guidance for use*. ISO.
- [13]. Khan, S. A. R., Godil, D. I., Jabbour, C. J. C., Shujaat, S., Razzaq, A., & Yu, Z. (2021). Green data analytics, blockchain technology for sustainable development, and sustainable supply chain practices: Evidence from small and medium enterprises. *Annals of Operations Research*. <https://doi.org/10.1007/s10479-021-04275-x>
- [14]. Kristoffersen, E., Blomsma, F., Mikalef, P., & Li, J. (2020). The smart circular economy: A digital-enabled circular strategies framework for manufacturing companies. *Journal of Business Research*, 120, 241-261. <https://doi.org/10.1016/j.jbusres.2020.07.044>
- [15]. Mishra, J. L., Chiwenga, K. D., & Ali, K. (2023). The role of reverse logistics in a circular economy for achieving sustainable development goals: A multiple case study of retail firms. *Production Planning & Control*, 35(12), 1490-1502. <https://doi.org/10.1080/09537287.2023.2197851>
- [16]. Nazir, S., Zhaolei, L., Mehmood, S., & Nazir, Z. (2024). Impact of green supply chain management practices on the environmental performance of manufacturing firms considering institutional pressure as a moderator. *Sustainability*, 16(6), 2278. <https://doi.org/10.3390/su16062278>
- [17]. Rajabzadeh, H., Rabiee, M., & Sarkis, J. (2024). Sourcing from risky reverse channels: Insights on pricing and resilience strategies in sustainable supply chains. *International Journal of Production Economics*, 276, 109373. <https://doi.org/10.1016/j.ijpe.2024.109373>
- [18]. Rogers, D. S., & Tibben-Lembke, R. S. (2001). An examination of reverse logistics practices. *Journal of Business Logistics*, 22(2), 129-148. <https://doi.org/10.1002/j.2158-1592.2001.tb00007.x>
- [19]. Sun, X., Yu, H., & Solvang, W. D. (2024). A two-level decision-support framework for reverse logistics network design considering technology transformation in Industry 4.0: A case study in Norway. *International Journal of Advanced Manufacturing Technology*, 134, 389-413. <https://doi.org/10.1007/s00170-024-14121-6>
- [20]. Tetteh, F. K., Kwateng, K. O., & Mensah, J. (2025). Enhancing carbon neutral supply chain performance: Can green logistics and pressure from supply chain stakeholders make any differences? *Sustainability Accounting, Management and Policy Journal*, 16(2), 521-551. <https://doi.org/10.1108/SAMPJ-08-2024-0884>