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The Effect Of Green Supply Chain Management And Supply Chain Management Performance On Sustainable Performance

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Abstrak

Penelitian ini menganalisis pengaruh variabel Manajemen Rantai Pasokan Hijau dan Manajemen Rantai Pasokan Kinerja terhadap dimensi lingkungan, ekonomi, dan sosial, serta dampaknya terhadap kinerja berkelanjutan. Hasil uji konfirmasi menunjukkan bahwa indikator konstruk yang digunakan signifikan untuk mengukur variabel laten endogen dan eksogen. Metode estimasi yang diterapkan adalah maksimum likelihood, yang mencari parameter optimal untuk menghasilkan kovariansi tertinggi. Model yang diusulkan memenuhi sebagian besar kriteria goodness of fit, meskipun tidak sesuai menurut kriteria chi square, tetapi dianggap layak berdasarkan konsensus yang ada. Pengujian hipotesis menunjukkan bahwa Manajemen Rantai Pasokan Hijau memiliki pengaruh positif terhadap lingkungan, ekonomi, dan sosial. Di sisi lain, Manajemen Rantai Pasokan Kinerja tidak memiliki pengaruh signifikan terhadap ekonomi. Analisis lebih lanjut menunjukkan bahwa 43,5% variabel ekonomi dapat dijelaskan oleh Manajemen Rantai Pasokan Hijau dan Manajemen Rantai Pasokan Kinerja, sedangkan sisanya 56,5% dipengaruhi oleh faktor lain. Temuan ini menekankan pentingnya penerapan Manajemen Rantai Pasokan Hijau dalam mendukung kinerja berkelanjutan.

***Keywords**: Manajemen Rantai Pasokan Hijau, Kinerja Rantai Pasokan, Sustainable Performance, Dampak Lingkungan, Structural Equation Modeling.*

Abstract

This research analyzes the influence of Green Supply Chain Management (Green SCM) and Performance Supply Chain Management (Performance SCM) variables on environmental, economic and social dimensions, as well as their impact on sustainable performance. The confirmatory test results show that the construct indicators used are significant for measuring both endogenous and exogenous latent variables. The estimation method applied is maximum likelihood (ML), which searches for optimal parameters to produce the highest covariance. The proposed model meets most of the goodness of fit criteria, although it is not fit according to the chi square criteria, but is considered feasible based on the existing consensus. Hypothesis testing shows that Green SCM has a positive effect on the environment, economy and social. On the other hand, SCM Performance has no significant effect on the economy. Further analysis indicates that 43.5% of the economic variables can be explained by Green SCM and Performance SCM, while the remaining 56.5% is influenced by other factors. These findings emphasize the importance of implementing Green SCM in supporting sustainable performance.

***Keywords**: Green Supply Chain Management, Supply Chain Performance, Sustainable Performance, Environmental Impact, Structural Equation Modeling.*

1. Introduction

In the era of globalization, the pace of business transformation has accelerated rapidly, demanding that companies adapt and innovate to remain competitive. Market pressures, technological advancements, and increasing customer expectations require firms to revise their strategies and operational models continuousl (Mail et al., 2019). Among various strategic functions, Supply Chain Management (SCM) plays a vital role in ensuring the efficiency, responsiveness, and sustainability of business operations (Tseng et al., 2022).

Despite its strategic importance, the implementation of SCM is often confronted with multiple challenges across the network. These include uncertainty in demand forecasting, disruptions in supply such as lead time variability, fluctuating prices, and inconsistency in raw material quality (Kulsaputro et al., 2025). Internally, firms may face issues like equipment breakdown, poor machine performance, and inconsistent product quality (Rodríguez Mañay et al., 2022). These factors, which often stem from multi-stakeholder interactions, significantly affect the efficiency and effectiveness of the

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supply chain (Stephen et al., 2025). Additionally, sudden changes in customer demand frequently disrupt procurement and production planning, leading to either material shortages or inventory overstock, both of which increase operational costs and reduce supply chain responsiveness (Nahason et al., 2024).

To overcome these challenges, companies must evaluate their supply chain performance through systematic measurement and continuous improvement (Özkanlısoy & Bulutlar, 2023). Supply chain performance is not only measured in terms of cost and delivery but also in how well it adapts to market changes, mitigates risks, and adds value to the customer (Safitri et al., 2025). Over time, SCM has evolved into a strategic approach that emphasizes the integrated flow of goods, information, and services, while increasingly incorporating environmental and sustainability objectives (Nguyen et al., 2023).

Recent developments in supply chain research have introduced the concept of Green Supply Chain Management (Green SCM), which integrates environmental practices into SCM functions, aiming to reduce environmental impact while maintaining or improving operational performance (Asnidar et al., 2024). Green SCM includes activities such as green purchasing, eco-friendly production processes, and sustainable logistics (Zain et al., 2023). Empirical studies have shown that such practices not only benefit the environment but also contribute to economic efficiency and social well-being (Ali et al., 2024; Hariyani et al., 2024). However, many organizations are still in the early stages of adopting these practices and require a deeper understanding of their performance implications (Rahman et al., 2020).

Although prior research has addressed various aspects of Green SCM and supply chain performance independently, few studies have simultaneously examined their combined impact on sustainable performance, particularly in terms of the triple bottom line: environmental, economic, and social outcomes (Bu et al., 2020). Moreover, most existing studies tend to focus on environmental performance alone, neglecting the holistic view of sustainability that encompasses broader organizational goals (Kumar Shetty & Subrahmanya Bhat, 2022; Lin et al., 2020). This gap in the literature highlights the need for an integrative analysis that considers both green initiatives and overall supply chain effectiveness.

This study seeks to address this gap by investigating the combined effects of Green Supply Chain Management and Supply Chain Performance on Sustainable Performance. By applying a Structural Equation Modeling (SEM) approach, the study aims to provide empirical evidence of the relationships between these constructs (Machado et al., 2023; Ning et al., 2025). The novelty of this research lies in its comprehensive framework that bridges environmental strategy and operational performance, offering practical insights for companies aiming to enhance sustainability in an increasingly competitive global landscape.

2. Research Methods

This study employs a quantitative research approach using Structural Equation Modeling (SEM) to examine the influence of Green Supply Chain Management (Green SCM) and Supply Chain Performance on Sustainable Performance, which includes environmental, economic, and social dimensions (Kumar et al., 2021; Yao et al., 2025) was selected due to its capability to analyze complex relationships between latent variables and test measurement as well as structural models simultaneously (Alhammadi et al., 2024; Herdianzah et al., 2024). Data were collected through a structured questionnaire distributed to professionals involved in supply chain operations across various manufacturing sectors. The indicators used in the questionnaire were adapted from previous validated studies and measured using a five-point Likert scale ranging from "strongly disagree" to "strongly agree."

The sampling method used was purposive sampling, targeting supply chain managers, procurement officers, logistics coordinators, and sustainability officers who have a direct role in implementing SCM practices. A minimum sample size of 150 respondents was targeted to meet the recommended criteria for SEM analysis using the maximum likelihood (ML) estimation method. Before the structural model testing, a confirmatory factor analysis (CFA) was conducted to ensure the validity and reliability of the measurement model. Furthermore, the model's goodness-of-fit was assessed using multiple fit indices such as CFI (Comparative Fit Index), RMSEA (Root Mean Square Error of Approximation), and GFI (Goodness-of-Fit Index) to evaluate the adequacy of the proposed model.

3. Results and Discussion

This section presents the results of the structural equation modeling analysis used to examine the impact of Green Supply Chain Management and Supply Chain Performance on Sustainable Performance. The findings include model fit indices, path coefficient significance, and interpretation of relationships among variables based on the empirical data collected.

3.1 Theoretical Model Framework

The theoretical framework in this study is developed to analyze the influence of Green SCM and Supply Chain Performance on Sustainable Performance, which includes three core dimensions: environmental, economic, and social. This framework reflects the growing emphasis on integrating environmental strategies with operational excellence to achieve long-term sustainability.

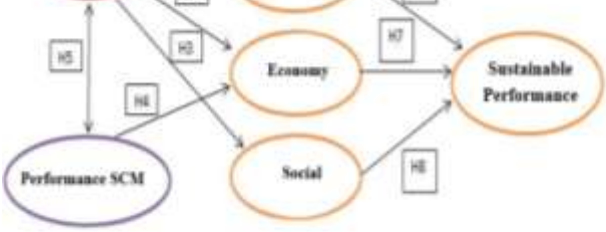

Figure 1: Theoretical Model Framework

The following will explain the theoretical framework of thought based on previous research to formulate hypotheses in this study.

a. Green Supply Chain Management

Green Supply Chain Management (Green SCM) is an approach that integrates environmental considerations into all stages of the supply chain process, including product design, material sourcing and procurement, manufacturing, distribution of final products to consumers, and end-of-life product management (Ali et al., 2024; Rahman et al., 2020; Runtuk et al., 2024). This approach has emerged in response to the increasing global awareness of environmental issues and serves as a strategic initiative to enhance long-term organizational competitiveness (Bu et al., 2020; Susanty et al., 2023).

Rather than focusing solely on operational efficiency, Green SCM emphasizes minimizing environmental impacts across the supply chain (Kumar Shetty & Subrahmanya Bhat, 2022; Lin et al., 2020). Its implementation has been shown to contribute positively to sustainable performance, particularly in three key dimensions: environmental, economic, and social (Habib et al., 2022; Hariyani et al., 2024; Machado et al., 2023; Rosyidah et al., 2022). Organizations that adopt Green SCM practices tend to improve resource efficiency, reduce waste and emissions, and enhance their corporate image among stakeholders. Therefore, Green SCM is considered a critical component in driving comprehensive sustainable performance in modern supply chain systems.

b. Performance Supply Chain Management

Supply Chain Management (SCM) performance has become a critical concern for organizations aiming to achieve global growth, operational excellence, and long-term profitability (Vegter et al., 2023). Effective supply chain performance requires decision-making across operational, tactical, and strategic levels, with each decision directly influencing key performance outcomes (Frederico et al., 2021; Mail et al., 2019). To evaluate and improve these outcomes, companies must utilize performance measurement systems that can assess the impact of key enablers and predict results through quantitative analysis of input-output relationships (A. Kumar et al., 2023).

From a managerial standpoint, understanding and monitoring supply chain performance is essential for identifying inefficiencies and driving continuous improvement (Khan et al., 2022). Evaluating supply chain performance allows organizations to align their operations with strategic objectives, enhance coordination across supply chain partners, and ultimately deliver greater value to customers. Within this context, supply chain performance reflects the competitive advantage that enables a company to differentiate itself from competitors in the marketplace (Gera et al., 2022). As such, performance measurement is not only a tool for operational assessment but also a strategic mechanism to reinforce competitive positioning and sustainable value creation (Dzikriansyah et al., 2023).

c. Sustainable Supply Chain Management (SSCM)

Sustainable Supply Chain Management (SSCM) is an integrated approach that incorporates environmental, economic, and social considerations into supply chain activities and decision-making processes (Kumar et al., 2023). Unlike traditional SCM, which focuses primarily on cost and efficiency, SSCM emphasizes the importance of minimizing environmental impact, ensuring social responsibility, and maintaining profitability (Hariyani et al., 2024). This includes practices such as reducing carbon emissions, using eco-friendly materials, promoting fair labor practices, and supporting community development (Adwiyah et al., 2023). By embedding sustainability principles into the entire supply chain from sourcing and production to distribution and disposal, SSCM enables organizations to create long-term value, enhance stakeholder trust, and contribute to broader global sustainability goals.

c.1 Environment

Environmental performance refers to the extent to which an organization minimizes its ecological footprint through its supply chain activities (Adwiyah et al., 2023). In the context of manufacturing and logistics, this includes efforts to reduce air emissions, manage water and solid waste efficiently, and lower the use of hazardous materials (Abualigah et al., 2023). Effective environmental practices in supply chain operations contribute to energy conservation, pollution reduction, and overall environmental stewardship, which are essential pillars in achieving sustainable performance.

c.2 Economy

Economic performance is a primary motivation for adopting green supply chain practices. It reflects the financial outcomes of environmentally and socially responsible strategies (Siems et al., 2021). Typical indicators of economic performance include increased profitability, growth in sales and market share, cost savings, and overall competitive advantage. Green SCM practices can lead to operational efficiencies and innovation that support both short-term gains and long-term economic sustainability (Khan et al., 2022).

c.3 Social

Social performance encompasses the social impacts and benefits resulting from supply chain practices (Hariyani et al., 2024). This includes improving product and corporate image, ensuring employee health and safety, fostering customer loyalty, and maintaining stakeholder trust (Nahason et al., 2024). Organizations that integrate social responsibility into their supply chains are more likely to strengthen relationships with customers, employees, and the broader community, thereby reinforcing their reputation and sustainability commitments.

In this study, the indicators for measuring SCM performance are based on the traditional approach, which is widely used. Performance indicators are given in the table below.

Table 1. Research Indicators

Construct	Indicator	Label Variable
Green SCM	Reduction source (SR)	GR1
	Eco-design (ED)	GR2
	Environmental management system (EMS)	GR3
	External environmental management (EEM)	GR4
	Environmental impact	GR5
	Environmental cost savings	GR6
SCM Performance	Reliability	PR1
	responsiveness	PR2
	Agility	PR3
	Asset	PR4
	Cost	PR5
Environment	Water	L1
	Air	L2
	Land	L3
	Energy	L4
Economy	Quality	E1
	Efficiency	E2
	Cost	E3
	Timeliness	E4
Social	Noise	S1
	Health	S2
	Employee satisfaction	S3
	Customer satisfaction	S4
Sustainable Performance	Structural and organizational changes	KB1
	Improving environmental regulations	KB2
	Cost reduction	KB3

3.2 Analysis Steps

a. Forming a relationship diagram between variables and indicators

The first step is to form a relationship diagram between variables and their indicators, as shown in the image below.

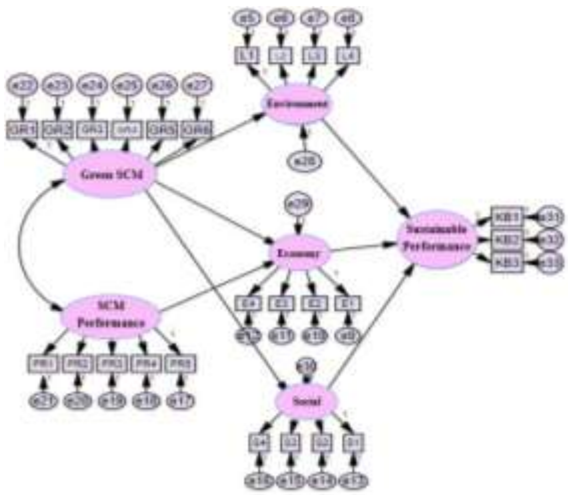

Figure 1: Initial model of the relationship between various variables and their indicators.

b. Confirmatory Analysis Factor for Exogenous and Endogenous Variables in the initial model.

To find out whether each indicator is significant for measuring the construct (latent variable), confirmatory factor analysis is used.

- Confirmatory Analysis Factor on Exogenous Variables

Confirmatory tests are carried out on exogenous variables, namely on the variables. Both variables are covariated, with the results of the diagram output and the estimated output from the confirmatory test given in figure 2.

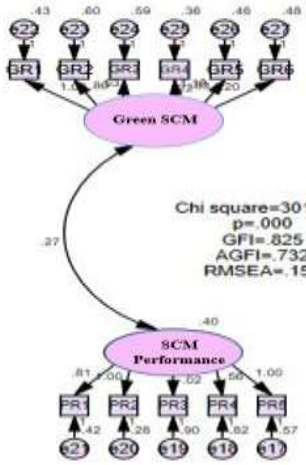

Figure 2: Exogenous Variable Diagram for Confirmatory Factor Test.

The results of the Chi Square test show that the model does not fit with a Chi Square value of 301.603 with a probability of P = 0.000 (less than 0.05) and reviewed from the criteria of GFI (0.825), AGFI (0.732) whose values are below 0.9 and RMSEA (0.150) whose values are above 0.08, then the model does not fit. To improve the fit model, an evaluation of the significance value of the regression weights is carried out.

Table 2: Regression Weights for Exogenous Variables

Variabel	Faktor	Estimate	S.E.	C.R.	P
PR5	<--F4	1.000			
PR4	<--F4	0.557	0.108	5.172	***
PR3	<--F4	-0.024	0.101	-0.241	0.809
PR2	<--F4	0.999	0.106	9.466	***
PR1	<--F4	0.814	0.099	8.232	***
GR1	<--F5	1.000			
GR2	<--F5	0.803	0.139	5.767	***
GR3	<--F5	0.534	0.125	4.283	***
GR4	<--F5	1.179	0.149	7.929	***
GR5	<--F5	0.825	0.129	6.382	***
GR6	<--F5	1.197	0.158	7.555	***

In Table 2, there is 1 insignificant indicator, namely indicators PR3 and F4, with a probability above the significance level of 0.001. Therefore, these indicators should be removed.

Table 3: Standardized Regression Weights For Exogenous Variables

Variabel	Faktor	Estimate	Variabel	Faktor	Estimate
PR5	<--F4	0.643	GR2	<--F5	0.434

PR4	←F4	0.364	GR3	←F5	0.307
PR3	←F4	-0.016	GR4	←F5	0.677
PR2	←F4	0.771	GR5	←F5	0.494
PR1	←F4	0.624	GR6	←F5	0.625
GR1	←F5	0.578			

However, the convergent validity value will be checked first, if the convergent validity value is less than 0.5 then the indicator will be removed from the analysis. The next step is to evaluate the convergent validity value, namely indicators with a factor loading less than 0.5 are declared invalid as a measure of the Green SCM and Performance SCM constructs.

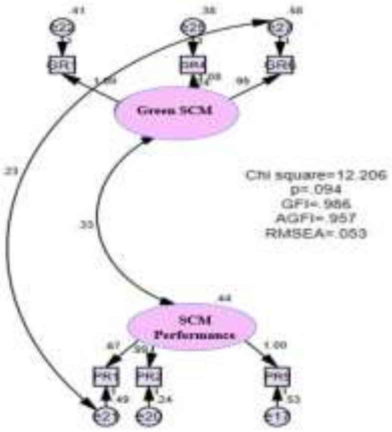

Figure 3: Final results of the confirmatory factor test for exogenous variables

From the results of standardized regression weights in Table 3, it is known that indicators PR4, PR3, GR2, GR3, GR5 have loading factors below 0.5 so they are removed from the initial model. And after modification to provide a relationship to e21 and e27, the results of the output of the confirmatory test of exogenous variables after several indicators are removed are given in the diagram in Figure 4. Based on the output in Figure 4, reviewed from the Chi Square value (12.206) with a probability of P = 0.094 indicates that the model is fit. Likewise, from the criteria of GFI (0.986), AGFI (0.957) and RMSEA (0.053) there are 4 out of 5 tests that show fit values. So the indicators in Diagram 4 will be used as indicators to compile a complete model.

- Confirmatory Analysis Factor on Endogenous Variables.

Confirmatory tests are conducted on endogenous variables, namely environmental, economic, and social variables. All endogenous variables are covariated, so that the results of the diagram and estimates for the confirmatory test are given in Tables 2 and 3.

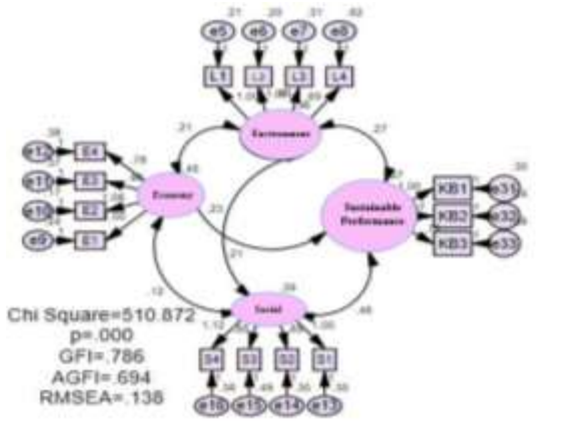

Figure 4: Endogenous Variable Diagram for Confirmatory Factor Test

The results of the Chi Square test show that the model is not fit with a p value = 0.000. However, with the criteria of GFI (0.786), AGFI (0.694) and RMSEA (0.138) the model is fit. To improve the model, a confirmatory test was carried out by reviewing the standard regression estimates and standardized regression weights as presented in Tables 4 and 5.

Table 4: Regression Weights for endogenous variables

Variabel	Faktor	Estimate	S.E.	C.R.	P
L1	←F1	1.000			
L2	←F1	1.072	0.083	12.984	***
L3	←F1	0.931	0.082	11.330	***
L4	←F1	0.651	0.094	6.916	***
E1	←F2	1.000			
E2	←F2	1.065	0.073	14.594	***
E3	←F2	0.961	0.078	12.343	***
E4	←F2	0.782	0.072	10.791	***
S1	←F3	1.000			
S2	←F3	0.853	0.080	10.717	***
S3	←F3	0.853	0.092	9.307	***
S4	←F3	1.117	0.097	11.469	***
KB1	←F6	1.000			
KB2	←F6	0.971	0.062	15.591	***
KB3	←F6	0.725	0.060	12.136	***

Table 4 Regression Weights for endogenous variables: (Group number 1 - Default model) From Table 4 below, it is known that all indicators are significant.

Table 5: Standardized Regression Weights for Endogenous Variables

Variabel	Faktor	Estimate	Variabel	Faktor	Estimate
L1	←F1	0.792	S1	←F3	0.729
L2	←F1	0.822	S2	←F3	0.702
L3	←F1	0.707	S3	←F3	0.609
L4	←F1	0.446	S4	←F3	0.753
E1	←F2	0.806	KB1	←F6	0.831
E2	←F2	0.865	KB2	←F6	0.852
E3	←F2	0.729	KB3	←F6	0.696
E4	←F2	0.651			

With the convergent validity analysis based on Table 5, several indicators with the smallest loading factor values are known, namely indicators L4, L3, KB3, S3, E2, E4. To obtain a smaller chi-square value, modification indices are also carried out. The Modification indices output is given in Table 6.

Table 6: Covariance: (Group number 1 - Default model)

			MI	Change of Partners
e14	<-->	e31	6.101	-.055

According to the suggestion from Table 6, the model revision was done by covarying the variables that would provide a theoretically justified decrease in chi square. This was done by covarying e14 with e31 with the modification index (MI) value.

The revised model results are given in Figure 6 with a Chi square value of 18.425 with a Probability of P = 0.362 stating that the model fits. Likewise, other criteria, namely GFI (0.985), AGFI (0.960) and RMSEA (0.018) support that the model fits. All indicators are convergent, so they are valid for measuring endogenous latent variables. These results will be used to compile a complete model.

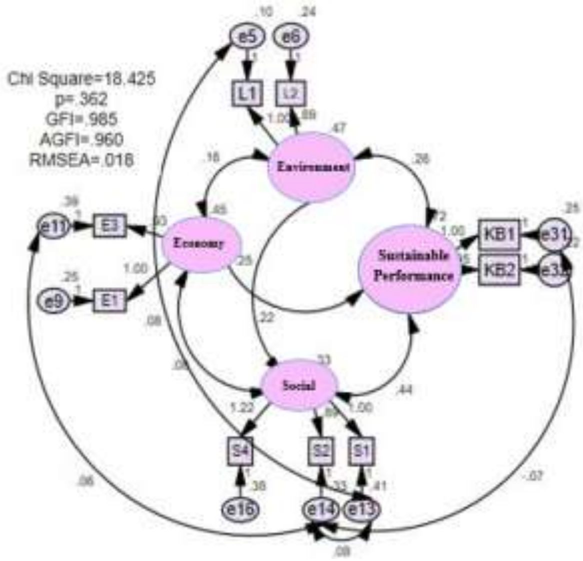

Figure 5: Final results of the confirmatory factor test for endogenous variables.

c. Estimation test on the full model.

From the results of the confirmatory test on exogenous and endogenous variables, a complete model is compiled by correlating all variables based on the theoretical framework and the proposed hypothesis. The complete output is given in Figure 6.

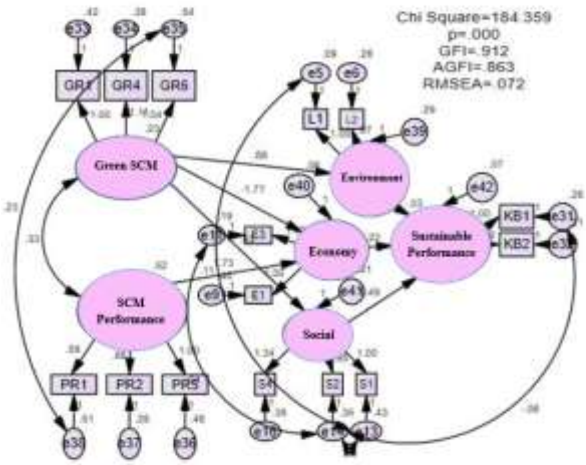

Figure 6: Complete Model Output

Normality evaluation is conducted to determine whether the data is normally distributed multivariately. Normality evaluation is conducted using the critical ratio skewness criterion of ± 2.58 at a significance level of 0.01. Assessment of normality is used as a requirement for assumptions that must be met with Maximum Likelihood. The results of the assessment of normality are shown in Table 7.

Table 7: Assessment of normality

Variabel	Min	Max	Skew	C.R.	Kurtosis	C.R.
PR1	1.000	5.000	-0.299	-2.000	0.199	0.667
PR2	1.000	5.000	-0.378	-2.533	0.159	0.534
PR5	1.000	5.000	-0.670	-4.484	0.155	0.518
GR6	1.000	5.000	-0.537	-3.596	0.223	0.747
GR4	1.000	5.000	-0.171	-1.146	0.137	0.459
GR1	1.000	5.000	-0.400	-2.696	0.366	1.226
KB2	1.000	5.000	-0.598	-4.037	0.399	1.067
KB1	1.000	5.000	-0.405	-2.711	-0.466	-1.559
S4	1.000	5.000	-0.406	-2.772	0.177	0.592
S2	1.000	5.000	-0.344	-2.347	0.269	0.899
S1	1.000	5.000	-0.547	-3.660	0.072	0.242
E3	1.000	5.000	-0.347	-2.377	0.073	0.247
E1	1.000	5.000	-0.244	-1.631	0.079	0.267
L2	1.000	5.000	-0.458	-3.070	0.209	0.705
L1	1.000	5.000	-0.683	-4.236	0.690	2.309
	Multivariate			78.022		28.332

These results indicate that univariately, there are many variables with critical ratio skewness values outside the range of ±2.58. Variables that are not normally distributed univariately are PR5, PR6, GR1, KB1, S2, S1, L2, and L1. Multivariately, the data is not normally distributed with a cr value of 28.332 which is much greater than 2.58. To obtain data with a normal distribution, it can be done by transforming the data into other function forms such as logarithms or square roots. However, in this study this cannot be done. In this study, an Outlier evaluation was carried out, namely looking for data that deviates greatly from other data. It is hoped that with this outlier, extreme data can be eliminated that causes the data to be abnormal.

- Outlier evaluation

An outlier is an observation condition of a dataset that has unique characteristics that look very different from other observations and appear in the form of extreme values, either for a single variable or a combination of variables. To find outliers, pay attention to the Mahalanobis distance value, which is used to measure the distance of the observation score to its centroid value. The results of the Outlier test are given in Table 8.

Table 8: Observations farthest from the centroid (Mahalanobis distance)

Obs	M d-squared	p1	p2	Obs	M d-squared	p1	p2	Obs	M d-squared	p1	p2	Obs	M d-squared	p1	p2
54	66,291	.000	.000	45	29,664	.013	.000	176	22,34	.089	.000	218	18,73	.226	.018
35	58,707	.000	.000	47	29,664	.013	.000	223	22,089	.106	.000	32	18,213	.252	.109
97	51,606	.000	.000	101	29,209	.015	.000	228	21,959	.109	.000	154	18,184	.253	.091
85	44,447	.000	.000	131	29,122	.016	.000	119	21,825	.113	.000	182	18,142	.255	.086
134	44,066	.000	.000	18	28,646	.018	.000	219	21,789	.113	.000	250	18,035	.261	.099
16	44,035	.000	.000	160	28,236	.020	.000	246	21,347	.128	.000	22	17,9	.268	.124
227	40,887	.000	.000	48	27,907	.022	.000	128	21,092	.137	.000	181	17,824	.272	.128
67	40,296	.000	.000	281	27,225	.027	.000	253	20,889	.140	.001	252	17,731	.277	.130
153	38,164	.001	.000	205	28,835	.030	.000	239	20,688	.147	.001	31	17,553	.287	.196
37	37,928	.001	.000	70	26,784	.031	.000	158	20,634	.149	.001	189	17,538	.288	.169
2	37,815	.001	.000	75	26,784	.031	.000	68	20,544	.152	.001	186	17,53	.288	.142
74	37,414	.001	.000	118	26,777	.031	.000	169	20,309	.164	.003	283	17,53	.288	.114
159	35,59	.002	.000	7	26,665	.052	.000	257	20,352	.166	.003	4	17,309	.301	.190
71	34,868	.003	.000	130	28,818	.032	.000	44	20,126	.167	.002	252	16,984	.321	.387
226	34,202	.003	.000	178	28,415	.034	.000	346	20,092	.168	.001	8	16,624	.342	.622
3	34,131	.003	.000	149	25,899	.039	.000	381	19,856	.178	.003	210	16,485	.351	.694
207	32,458	.006	.000	124	25,711	.041	.000	49	19,852	.178	.002	212	16,391	.357	.711
121	32,454	.006	.000	58	24,594	.056	.000	221	19,685	.185	.004	288	16,071	.377	.872
73	32,232	.006	.000	167	24,256	.061	.000	151	19,657	.185	.002	46	16,021	.381	.868
241	31,669	.007	.000	105	24,065	.066	.000	58	19,648	.188	.002	225	15,968	.384	.857
240	31,061	.009	.000	81	23,813	.072	.000	102	19,634	.188	.001	108	15,779	.397	.822
157	30,923	.009	.000	235	23,025	.084	.000	39	18,92	.237	.029	238	15,512	.415	.971
95	30,096	.012	.000	222	22,958	.085	.000	27	18,91	.238	.022	237	15,462	.419	.970
61	29,894	.012	.000	247	22,855	.088	.000	155	18,907	.238	.018	169	15,283	.431	.985
214	29,826	.013	.000	175	22,482	.096	.000	249	18,746	.221	.024	58	15,207	.437	.987

From Table 8, it is known that observation no. 54 provides the furthest distance from the centroid with a Mahalanobis distance value. of 66,291. Column p1 shows, assuming normality, the probability of d–d-squared above the value66,291and so on down to no. 128 is 0.000. The way to eliminate outlier data is to remove data that has a value of 0.000. Outlier results are stored in the File, Data after Outlier. Sav. Data that is free from outliers is used to test the complete model.

- Complete Model Parameter Value Estimation

From the output results in Figure 11, it is known that in terms of the Chi Square Criteria, the model is not yet fit because the p-value = 0. By replacing the data from the initial data-sav file to the data s.outlier-sav file, and correcting it with modification indices as given in Table 9, the Final model is obtained as in Figure 8.

Table 9: Model Parameter Value Estimation

Relasi	M.I.	Par Change
e41 <--> Performance_SCM	6.456	-0.024
e41 <--> Green_SCM	6.605	0.017
e39 <--> Performance_SCM	4.965	-0.025
e39 <--> Green_SCM	5.016	0.017
e39 <--> e41	29.678	0.105
e37 <--> e38	5.546	0.055
e35 <--> e41	8.272	0.061
e35 <--> e39	6.544	0.065
e34 <--> Performance_SCM	4.353	-0.025
e34 <--> Green_SCM	4.343	-0.017
e33 <--> Performance_SCM	6.473	0.032
e33 <--> Green_SCM	6.526	-0.022
e33 <--> e41	7.314	-0.058
e32 <--> e37	4.738	0.044
e14 <--> e39	10.637	0.072
e13 <--> e37	7.164	-0.059
e13 <--> e39	8.959	0.071
e11 <--> e39	8.595	-0.071
e11 <--> e38	6.183	-0.063
e11 <--> e36	8.947	0.084
e10 <--> e36	6.500	0.056
e9 <--> e39	4.506	0.054
e5 <--> e41	9.168	0.046
e5 <--> e14	7.424	0.047

From Figure 7, it is obtained that the Chi Square value has decreased with a fixed change value of 87.615, the probability value of p = 0.055. From the Chi Square criteria, the model is considered fit, and using other criteria such as GFI (0.960), AGFI (0.929), and RMSEA (0.033), the model is considered Fit. So that the model will be analyzed for its parameter estimates to see whether the hypothesis proposed in this study is proven.

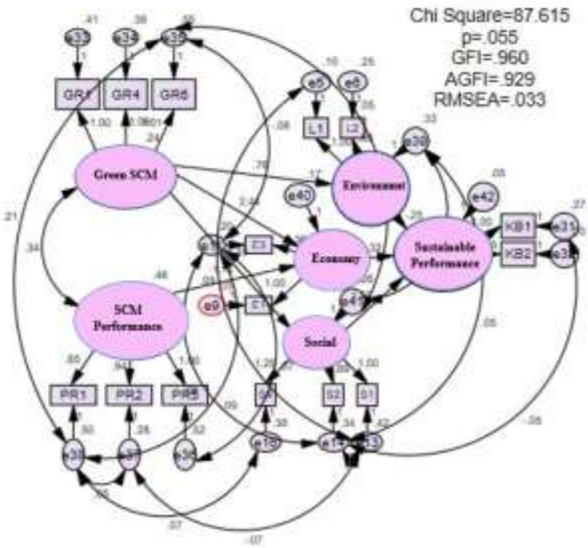

Figure 7: Final Model Output

It is known that the influence of the relationship between the Performance SCM variable and the Economy is not significant because the p-value (0.709) is greater than 0.001. Likewise, for the relationship between the Economy variable and Green SCM, the Sustainable Performance variable with the Environment is not significant because the P value is above 0.001.

3.3 Discussion

From the development of the proposed model using the SEM method, it can be known that the estimated strength of the relationship between various variables and significant indicators for the success of SCM Performance as hypothesized in the proposed model. The estimation method used is Maximum Likelihood (ML), which is by finding the parameter value that is most likely to produce the highest covariance or correlation of the existing data. According to some experts, this approach can be used for data that has problems with normality.

However, this ML method is very sensitive to non-normality of data so that other estimation methods such as Weighted least Square (WLS), Generalized Least Squares (GLS) and Asymmetrically Distribution Free (ADF) have emerged. The model fit test in this report uses several criteria, including Chi Square, GFI, AGFI and RMSEA. Although the final model obtained a high Chi square value (149.247) with zero probability, because several other criteria were met with GFI and AGFI values above 0.9 and RMSEA below 0.08, the model was considered suitable. This is because there is no agreement on which goodness of fit criteria are truly fit.

High chi square values can be caused by data that is not normally distributed multivariately. High chi square values relative to the degree of freedom indicate that the observed and predicted covariance or correlation matrices are significantly different and this results in a probability (p) that is smaller than the significance level (σ). Efforts to reduce chi square are made by modifying the model (Modification Indices), but p remains smaller than the significance level (σ). To meet the assumption requirements that must be met with maximum likelihood, this report conducts data normality testing.

Green SCM has a positive effect on the Environment with a standardized regression coefficient of 0.539 (H1 is accepted). Likewise, for other hypotheses, all are accepted except Performance SCM has a positive effect on the Economy with a standardized regression coefficient of -1.396 (H4 is rejected), and the Environment has a positive effect on Sustainable Performance is rejected because the standardized regression coefficient value is -0.201 (H6 is rejected) (Dzikriansyah et al., 2023).

Squared Multiple Correlations, the coefficient of determination of each variable can be seen. For example, the economic variable has an estimated value of 0.435, meaning that the economic variable that can be explained by green SCM and Performance SCM is 43.5% while 56.5% is in the environmental, economic, social and sustainable performance variables in this report (Abualigah et al., 2023). The Squared Multiple Correlations value that is smaller than 0.5 indicates that the antecedent variable cannot explain the consequent variable (Adwiyah et al., 2023). Based on the model output in Table 12, it can be concluded that all antecedent variables cannot explain the consequent variable because the R2 value is smaller than 0.5.

The output of total effect, direct effect and indirect effect of each variable in the model. From the output, the magnitude of direct and indirect influence between variables can be known. For example, to find out the direct, indirect and total effect on the sustainability performance variable, there is an indirect relationship between the SCM Performance variable and sustainable performance through the economy: SCM performance → Economy → Sustainable performance (Gera et al., 2022). There is no indirect relationship in the Standardized direct effect variable table (Table 9), the magnitude of the indirect effect from SCM performance to the economy is -1.396 and the indirect effect from the economy to sustainable performance is 0.213. So the magnitude of the indirect effect from the SCM Performance variable to sustainable performance is (-1.396) (0.213) = -0.297. This value of Standardized Total Effects is seen in Table 18 Standardized Indirect Effects (Khan et al., 2022). The magnitude of the total effect of the green SCM variable to sustainable performance is -0.297. The value of this total effect can be seen Standardized Total Effect in the sustainable performance row (Nguyen et al., 2023). In the study for the direct relationship between the SCM Performance Variable and sustainable performance, there is no direct relationship. This also applies to other variables according to the values given by the output table.

In the Final Model Output Diagram in Figure 7, there is a correlation between error measurements on several indicators. This can occur because two or more latent variable indicators in a model are systematically influenced by a factor that is not explicitly included in the model.

4. Conclusion

Based on the analysis results, it can be concluded that the construct indicators used are statistically significant in measuring both endogenous and exogenous latent variables. Parameter estimation was performed using the Maximum Likelihood (ML) method, which, despite its sensitivity to non-normal data, provides optimal estimation under most conditions. The proposed model is considered fit according to several goodness-of-fit criteria, including the Goodness of Fit Index (GFI), Adjusted GFI (AGFI), Root Mean Square Error of Approximation (RMSEA), and Probability level, although it does not meet the Chi-Square criterion. The hypothesis testing results show that Green SCM has a positive effect on the environment with a standardized regression coefficient of 0.539 (H1 accepted), on the economy with a coefficient of 2.144 (H2 accepted), and on the social dimension with a coefficient of 0.397 (H3 accepted). Conversely, SCM Performance has no significant effect on the economy (coefficient = -1.396; H4 rejected), and the environment does not significantly affect sustainable performance (coefficient = -0.201; H6 rejected). However, both economic (coefficient = 0.213; H7 accepted) and social factors (coefficient = 0.994; H8 accepted) significantly influence sustainable performance. The coefficient of determination (R^2) for the economy variable is 0.435, indicating that only 43.5% of its variance is explained by Green SCM and SCM Performance. For future research, it is recommended to include additional variables such as green technology innovation, government regulation, or organizational culture. Employing alternative estimation methods like Generalized Least Squares (GLS) or Asymptotically Distribution-Free (ADF), along with mixed methods, could provide more comprehensive insights into Green SCM and sustainable performance across various sectors.

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