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Does Artificial Intelligence Based Green Supply Chain Improve Sustainable Economic Performance? Evidence from Indonesian Firms

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ABSTRACT

This study examines the role of artificial intelligence adoption in optimizing green supply chains and how its practices can improve sustainable economic efficiency in the Indonesian manufacturing sector. A survey was conducted among manufacturing companies that have integrated AI into their green supply chains. The study employed SEM processed using AMOS, resulting in the finding that AI adoption significantly improves GSC practices, which in turn significantly contributes to sustainable economic efficiency. Furthermore, the results confirm that GSC acts as a mediating between artificial intelligence and sustainable economic efficiency. This study highlights the strategic importance of incorporating innovative AI use in sustainable practices, offering practical insights for managers to align AI applications with green objectives. For policymakers, these findings underscore the potential of AI-powered GSC as a catalyst for national sustainability and decarbonization efforts, emphasizing the need for standardized sustainability policies, incentives, and metrics to create sustainable economic efficiency in Indonesia.

Keywords: Efficiency; Green Supply Chain; Sustainable Economic Efficiency; Artificial Intelligence; Sustainability
JEL Classifications: M15; Q56; O33; Q55

1. INTRODUCTION

Escalating climate risks and the tightening of environmental regulations, particularly those related to carbon emissions, have intensified the pressure on firms to embed sustainability principles throughout their supply chains. In Indonesia, this pressure is increasingly evident through government commitments to emissions reduction, the expansion of ESG-based disclosure requirements, and growing scrutiny from investors and international trading partners. As a response, many companies have begun to adopt green supply chain practices aimed at reducing environmental impact while maintaining operational efficiency. However, in practice, the implementation of GSCM in Indonesia remains uneven and faces persistent operational constraints.

Empirically, Indonesian firms continue to struggle with inaccurate demand forecasting, suboptimal resource allocation, and rising energy as well as logistics costs. These inefficiencies not only weaken environmental performance but also undermine economic sustainability by increasing operational risks and eroding competitiveness. Such challenges suggest that conventional supply chain management approaches may no longer be sufficient to support sustainability-oriented objectives, particularly in emerging economies characterized by market volatility and infrastructure limitations.

Recent international studies increasingly point to artificial intelligence (AI) as a transformative tool capable of addressing these limitations. Prior research demonstrates that AI-based techniques such as machine learning, real-time data analytics, and metaheuristic optimization can significantly enhance supply chain planning, logistics efficiency, and waste reduction, Chen et al. (2024); Qu et al. (2024); Li et al. (2024); Toderas (2025). Moreover, systematic evidence indicates that AI adoption contributes to sustainability outcomes aligned with the Sustainable Development Goals, especially through improved resource efficiency and carbon footprint mitigation Toderas (2025). From a resilience perspective, AI and big data analytics have also been shown to optimize routing decisions, reduce fuel consumption, and lower emissions, while simultaneously improving delivery reliability Ali et al. (2024); Lee and Trimi (2024).

Despite these advances, several critical research gaps remain. First, the majority of existing studies are concentrated in developed economies, limiting the generalizability of findings to emerging markets such as Indonesia, where institutional settings, data availability, and technological readiness differ substantially. Second, prior research predominantly emphasizes operational or environmental outcomes, while the economic dimension of sustainability particularly sustainable economic efficiency receives comparatively less empirical attention. Third, empirical evidence examining AI as a strategic enabler of GSCM, rather than merely a technological tool, remains limited, especially within firm level quantitative analyses.

Addressing these gaps, the present study aims to examine the role of artificial intelligence in supporting the implementation of green supply chain management in Indonesian firms and to assess its impact on sustainable economic efficiency. By focusing on Indonesia as an emerging economy, this research seeks to extend the existing literature by providing empirical evidence on how AI driven GSCM strategies contribute not only to environmental improvements but also to economically sustainable outcomes. The findings are expected to offer both theoretical contributions to the GSC and AI nexus and practical insights for managers and policymakers seeking to balance sustainability objectives with economic performance.

2. LITERATURE REVIEW

This study is grounded primarily in the Resource-Based View (RBV), which posits that firms achieve sustainable competitive advantage by developing valuable, rare, inimitable, and non-substitutable resources and capabilities (Barney, 1991). Within this perspective, artificial intelligence enabled capabilities such as advanced analytics, real-time decision making, and predictive optimization can be regarded as strategic resources that enhance firms' ability to manage complex and dynamic supply chains. When embedded in green supply chain management (GSCM) practices, these AI capabilities enable firms to improve operational efficiency while simultaneously addressing environmental challenges.

Extending the RBV to environmental contexts, the Natural Resource Based View (NRBV) emphasizes that environmental capabilities, including pollution prevention, product stewardship, and sustainable development, can serve as sources of competitive advantage Shrivastava and Hart (1995). In line with the NRBV, AI-based GSCM facilitates eco-efficient processes by optimizing resource use, reducing waste, and lowering emissions, thereby aligning environmental responsibility with economic value creation. From a technological perspective, artificial intelligence, particularly machine learning, enables systems to learn from large volumes of data, identify patterns, and support more accurate and timely decision making in complex supply chain environments (Sammut and Webb, 2017). Consequently, firms that effectively integrate AI into their GSCM practices are more likely to achieve superior environmental and economic performance, consistent with the core propositions of the NRBV (Hart, 1995).

The concept of sustainability underpinning this study is further informed by the Brundtland Commission's definition of sustainable development as development that meets present needs without compromising the ability of future generations to meet their own needs (WCED, 1987). This perspective highlights the intergenerational dimension of sustainability and provides a normative foundation for integrating environmental considerations into economic decision-making.

Complementing this view, the green growth framework articulated by the Organization for Economic Co-operation and Development (OECD) underscores the importance of fostering economic growth while maintaining the resilience of natural assets and ecosystem services OECD (2011). From this standpoint, AI-driven GSCM strategies represent a mechanism through which firms can decouple economic performance from environmental degradation.

Finally, the notion of eco-efficiency, as promoted by the World Business Council for Sustainable Development (WBCSD), reinforces the linkage between environmental and economic outcomes by emphasizing the creation of greater value with reduced environmental impact WBCSD, (2000). AI enabled optimization of logistics, energy use, and material flows within supply chains exemplifies how firms can operationalize eco-efficiency in pursuit of sustainable economic performance.

2.1. Artificial Intelligence

Artificial intelligence refers to a class of computational technologies that enable systems to perceive information, learn from data, and perform tasks that typically require human cognitive abilities, including reasoning and decision-making Russell and Norvig (2021). Within supply chain operations, AI applications extend beyond automation to include advanced demand prediction, adaptive inventory management, route and network optimization, condition-based maintenance, and the simulation of complex processes through digital twin technologies (Chen et al., 2024; Teixeira et al., 2025). By integrating large-scale data analytics with learning algorithms, AI enhances managerial decision quality, reduces operational slack, and supports the achievement of environmental objectives embedded in green supply chain initiatives.

2.2. Green Supply Chain

Green supply chain management is a managerial approach that integrates environmental considerations into traditional supply chain activities, guided by the principles of the Triple Bottom

Line, which advocates simultaneous attention to economic, environmental, and social performance Elkington (1997). GSC practices span the entire supply chain, including environmentally responsible sourcing, sustainable product and process design, cleaner production systems, green logistics, and effective reverse logistics mechanisms Srivastava (2007) (Srivastava, 2007; Seuring and Müller, 2008). Through these practices, firms seek to reduce material waste, lower emissions, and improve energy utilization while maintaining operational effectiveness.

2.3. Sustainable Economic Efficiency

Sustainable economic efficiency reflects a firm's capability to achieve superior economic outcomes while limiting the consumption of natural resources and environmental degradation OECD (2011); WBCSD (2000). Rather than focusing solely on cost minimization, this concept emphasizes the optimization of value creation relative to environmental impact. Common indicators include reductions in logistics and energy expenditures, improvements in resource productivity, and lower carbon emission intensity. Accordingly, firms exhibiting high sustainable economic efficiency are able to deliver economic gains with a smaller ecological footprint.

2.4. Artificial Intelligence and Sustainable Economy Efficiency

Artificial intelligence (AI) is increasingly viewed as an economically strategic technology that enhances decision-making quality and efficiency within supply chain management. In this context, AI supports key operational functions such as demand estimation, inventory optimization, routing and scheduling decisions, predictive maintenance, and the simulation of supply chain processes through digital twin systems Chen et al. (2024) Qu et al. (2024); Teixeira et al. (2025); Chen et al. (2025). By improving information accuracy and reducing coordination inefficiencies, AI enables firms to operate supply chains more efficiently while aligning with the environmental objectives of green supply chain.

From a conceptual standpoint, AI refers to intelligent systems designed to perceive their operational environment and undertake actions that maximize the achievement of predefined objectives Russell and Norvig (2021). This definition is complemented by policy-oriented perspectives that emphasize AI as machine-based systems capable of autonomous analysis and adaptive responses to environmental inputs in pursuit of targeted outcomes (High-Level Expert Group on AI, European Commission, 2018). These definitions highlight AI's relevance not only as a technological innovation but also as an institutional instrument shaping firm-level economic behavior.

In economic terms, the adoption of AI in supply chain activities contributes directly to efficiency gains by reducing forecasting errors, optimizing resource allocation, and lowering logistics and energy costs. At the same time, improved operational efficiency often results in lower emission intensity and reduced environmental externalities. This dual outcome reflects the principle of sustainable economic efficiency, which emphasizes achieving higher economic value with lower environmental costs OECD (2011). Accordingly, AI driven supply chain practices represent a mechanism through which firms can reconcile productivity enhancement with environmental sustainability.

Empirical studies provide consistent evidence supporting this argument Chen et al. (2024). Document that AI-based logistics optimization improves resource utilization and contributes to emission reductions, indicating efficiency gains with environmental co-benefits. Similarly, Li et al. (2024) find that the application of generative AI in supply chains enhances operational accuracy and reduces costs, leading to improved sustainable performance. Building on these findings, this study formulates the following hypothesis:

H_1: Artificial Intelligence has a positive effect on sustainable economic efficiency.

2.5. Green Supply Chain and Sustainable Economic Efficiency

Green supply chain management (GSCM) is commonly understood as a comprehensive managerial approach that embeds environmental considerations across the entire supply chain, ranging from product and process design to sourcing decisions, manufacturing activities, distribution systems, and the management of product returns Srivastava (2007). Within the broader concept of sustainable supply chain management (SSCM), these environmental initiatives are coordinated with economic and social objectives to ensure balanced and long-term performance in line with the triple bottom line (TBL) framework Seuring and Müller (2008); Carter and Rogers (2008).

While artificial intelligence may exert a direct influence on sustainable economic efficiency, its impact is more likely to materialize through the transformation of supply chain practices. GSCM serves as an important transmission mechanism through which AI generated insights are converted into environmentally and economically efficient operational outcomes. Rooted in the TBL perspective, GSCM emphasizes environmentally responsible sourcing, eco-design, cleaner production processes, and efficient logistics systems Elkington (1997); Seuring and Müller (2008). AI supports the effective execution of these practices by enhancing information transparency, enabling real-time monitoring, and automating complex decision processes, thereby strengthening the sustainability orientation of supply chain operations.

Event syntheses of the literature provide strong support for this indirect relationship. Qu et al. (2024) show that AI based applications significantly enhance the effectiveness of GSCM initiatives in achieving sustainability-related objectives. Earlier empirical studies also demonstrate that GSCM acts as a critical conduit through which managerial innovations translate into superior performance outcomes, Zhu and Sarkis (2008), and Lai (2008). Evidence from emerging economies further reinforces this mechanism. In the Indonesian context, Dwidienawati et al. (2025) find that AI enabled digitalization amplifies the role of GSC in improving both economic efficiency and environmental performance. Similar patterns are observed across ASEAN countries, where digital and AI driven supply chain practices strengthen the contribution of GSCM to sustainable performance outcomes Ngunyen and Bui (2023); Tran and Le (2023); Pham and Dao (2023) highlighted that AI enabled digitalization strengthens GSCM's role in driving economic and environmental efficiency. Thus, we hypothesize:

H_2: Green supply chain mediates the relationship between artificial intelligence and sustainable economic efficiency.

3. METHODS

This study adopts a quantitative research design with an explanatory approach to analyze how artificial intelligence (AI) capabilities and applications contribute to the optimization of green supply chain (GSC) practices and how these practices subsequently affect sustainable economic efficiency. The explanatory design is employed to test hypothesized causal relationships among variables based on established theoretical and empirical foundations (Table 1).

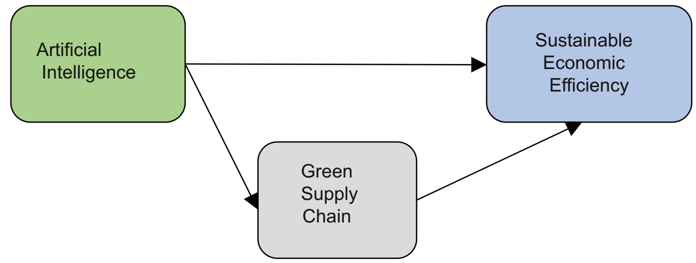
The measurement items used in this study were adapted from well-established prior research to ensure content validity. Artificial Intelligence is conceptualized as machine-based systems capable of interpreting environmental inputs and acting autonomously to achieve predetermined objectives Russell and Norvig (2021). In the context of supply chain management, AI applications encompass machine learning–based demand forecasting, routing and scheduling optimization, predictive maintenance, and the utilization of digital twin technologies to enhance operational planning and control Chen et al. (2024); Teixeira et al. (2025).

Green supply chain practices are defined as the systematic integration of environmental considerations into key supply chain activities, including procurement, production processes, logistics operations, and reverse logistics systems Srivastava (2007); Seuring and Müller (2008); Li et al. (2024). Meanwhile, sustainable economic efficiency refers to a firm's capability to create economic value while minimizing environmental impact, reflecting the principle of achieving higher productivity with lower ecological costs WBCSD (2000); OECD (2011); Seuring and Müller (2008).

The study population consists of employees from firms operating across various industrial sectors. Respondents were selected using a purposive sampling technique, as the study specifically targeted employees working in organizations that have implemented AI technologies within their green supply chain activities. Data were collected through an online survey, resulting in 500 usable responses from 738 distributed questionnaires, yielding a response rate of approximately 67.7%.

To test the proposed hypotheses and examine the structural relationships among variables, this study employs structural equation modelling (SEM) using AMOS software. The analysis is based on primary data obtained from the questionnaire responses. In the proposed research model, Artificial Intelligence capabilities and Green Supply Chain practices are treated as independent variables, organizational capability is included as a moderating variable, and sustainable economic efficiency serves as the dependent variable. The conceptual framework illustrating these relationships is presented in Figure 1.

Figure 1: Theoretical model



4. RESULTS AND DISCUSSION

The results of the confirmatory factor analysis indicate that all latent constructs meet the required standards for convergent validity and internal consistency reliability. The values of composite reliability (CR) and average variance extracted (AVE) for each construct exceed the recommended cutoff levels of 0.70 and 0.50, respectively, suggesting satisfactory measurement quality (Figure 2).

Specifically, the construct of artificial intelligence adoption (ADO) demonstrates strong reliability and convergent validity, with a CR value of 0.949 and an AVE of 0.788. Similarly, green supply chain management (GSCM) exhibits robust measurement properties, reflected by a CR of 0.944 and an AVE of 0.772. The construct of sustainable economic efficiency (SEE) also satisfies the recommended thresholds, with a CR of 0.923 and an AVE value of 0.710. A comprehensive overview of these results is provided in Table 2.

Most of the standardized factor loadings are above the recommended cutoff value of 0.70, indicating strong associations between the observed indicators and their respective latent constructs. Although one indicator exhibits a relatively lower loading (EFI1 = 0.606), this value still exceeds the minimum acceptable threshold of 0.50, and therefore the indicator is retained in the measurement model. Detailed information on item-level standardized loadings is presented in Table 3.

The measurement models for all constructs exhibit satisfactory levels of overall model fit. The majority of the goodness-of-fit indicators fall within the recommended good fit criteria, as reflected by high values of the comparative fit index (CFI = 0.993-1.000), Tucker–Lewis index (TLI = 0.983-1.002), and Goodness-of-Fit index (GFI = 0.989-0.998), along with low residuals indicated by the Root Mean Square Residual (RMR = 0.006-0.019) and acceptable values of the root mean square error of approximation (RMSEA = 0.000-0.054).

Although the Parsimony Goodness-of-Fit Index (PGFI ≈ 0.20-0.27) appears relatively modest, such values are commonly observed in models with limited structural complexity and do not undermine the overall adequacy of model fit. A detailed presentation of the

Figure 2: Adjusted relationship between the latent variables and their observed indicators

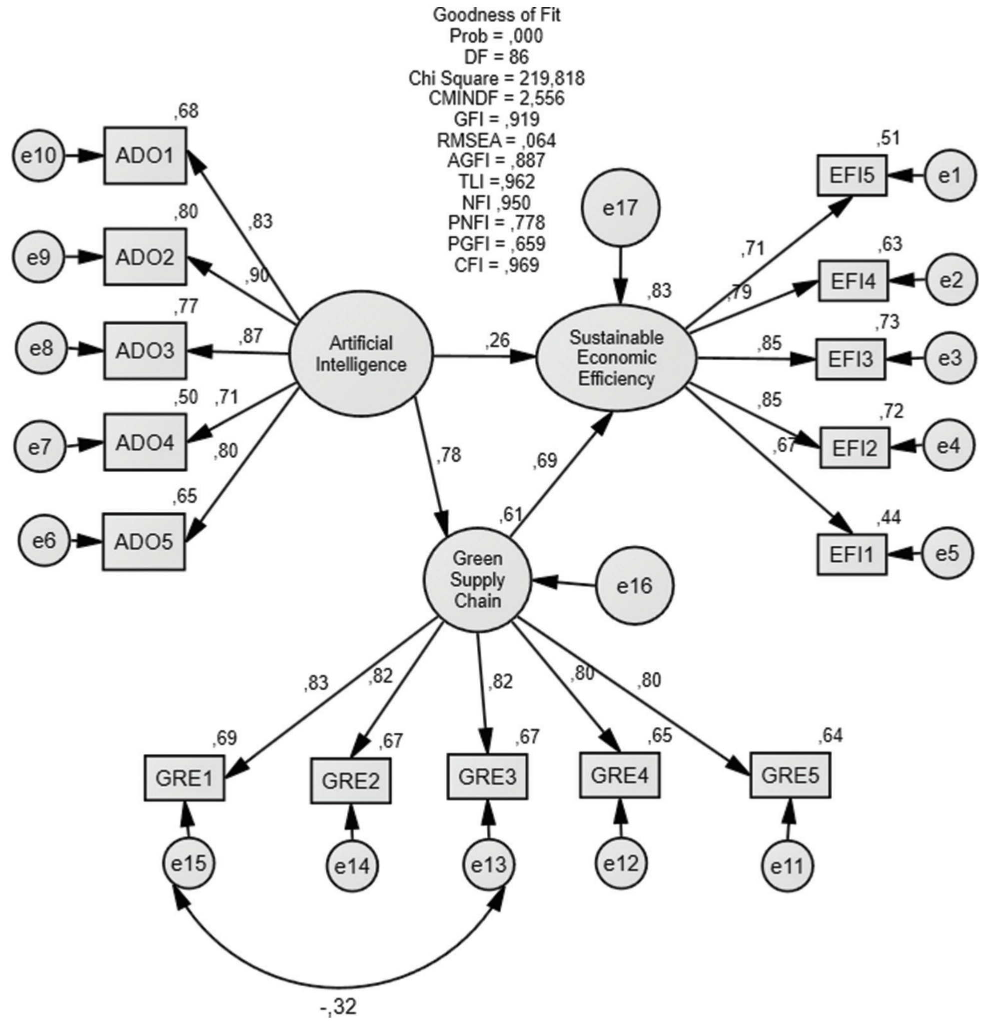


Table 1: Variables and measurements

Item		Sources
Artificial intelligence		
ADO1	1. My company has implemented AI technology in its supply chain.	AbdEllatif and Baazeem (2025); Wamba-Taguimdje et al. (2020)
ADO2	2. AI is used to accurately predict customer demand.	
ADO3	3. AI-based systems are used in inventory/logistics management.	
ADO4	4. AI helps accelerate operational decision-making.	
ADO5	5. AI investments improve the efficiency of our supply chain activities.	
Green supply chain		
GRE1	1. We implement green procurement practices.	Zhu and Sarkis (2008); Srivastava (2007)
GRE2	2. Our production processes are designed to reduce environmental impact.	
GRE3	3. We partner with suppliers who are environmentally committed.	
GRE4	4. We use an environmental tracking system throughout the supply chain.	
GRE5	5. Our company implements the 3R principle (reduce, reuse, recycle) in product distribution.	
Deficiency sustainable economy		
EFI	1. The implementation of AI and GSCM has reduced our logistics and operational costs.	Chen et al. (2025)
EFI2	2. Our company has been able to improve energy efficiency in our distribution and production processes.	
EFI3	3. Our company's economic performance has improved through the implementation of environmentally friendly technologies.	
EFI4	4. We have been able to achieve our economic goals without compromising environmental sustainability.	
EFI5	5. Digital innovation and green processes contribute to our company's long-term competitiveness.	

fit statistics for each construct is provided in Table 4.

1. Artificial Intelligence has a positive and significant impact on the green supply chain, with an estimated value of 0.765, a C.R. of 13.984 (>1.96), and a significance level of 0.000 (<0.05). This means that improving AI will increase green supply chain implementation by 76.5%.
2. The green supply chain has a positive and significant impact on sustainable economic efficiency, with an estimated value

of 0.563, a C.R. of 9.670 (>1.96), and a significance level of 0.000 (<0.05). Therefore, improving the green supply chain will increase sustainable economic efficiency by 56.3%.

3. Artificial intelligence (AI) also has a positive and significant impact on sustainable economic efficiency, with an estimated value of 0.210, a C.R. of 4.517 (>1.96), and a significance level of 0.000 (<0.05). This indicates that improving AI will directly increase sustainable economic efficiency by 21.0%.

Table 2: Convergent validity

Construct/variable	CR (≥0.70)	AVE (≥0.50)
AI adoption (ADO)	0.949	0.788
Green supply chain (GRE)	0.944	0.772
Sustainable economic efficiency (EFI)	0.923	0.710

Table 3: Cross-loadings

Item	Standardized loading	Result
AI adoption (ADO)		
ADO1	0.824	Valid
ADO2	0.899	Valid
ADO3	0.853	Valid
ADO4	0.717	Valid
ADO5	0.800	Valid
Green supply chain (GRE)		
GRE1	0.819	Valid
GRE2	0.801	Valid
GRE3	0.845	Valid
GRE4	0.791	Valid
GRE5	0.781	Valid
Sustainable economic efficiency (EFI)		
EFI1	0.606	Valid
EFI2	0.787	Valid
EFI3	0.884	Valid
EFI4	0.799	Valid
EFI5	0.726	Valid

Table 4: Model fit

Fit index	SEM	General criteria	Interpretation
Comparative fit index (CFI)	0.995	≥0.90 (good fit)	Good fit
Tucker-Lewis index (TLI)	0.988	≥0.90 (good fit)	Good fit
Goodness-of-fit index (GFI)	0.992	≥0.90 (good fit)	Good fit
Root mean square residual (RMR)	0.011	≤0.08 (good fit)	Good fit
Root mean square error of approx. (RMSEA)	0.054	≤0.08 (good fit)	Good fit
Parsimony goodness-of-Fit index (PGFI)	0.265	≥0.90 (good fit)	Good fit

The result indicates a substantial indirect effect of artificial intelligence (AI) on sustainable economic efficiency through green supply chain practices with a standardized coefficient of 0.542. This finding suggests that the primary contribution of AI to sustainable economic efficiency is transmitted via its influence on the green supply chain, highlighting the mediating role of environmentally oriented supply chain practices. In practical terms, higher levels of AI adoption enhance Green Supply Chain implementation, which subsequently leads to an improvement in sustainable economic efficiency of approximately 54.2%.

Further evidence of the model's explanatory strength is provided by the squared multiple correlations (SMC). The SMC value for the green supply chain construct is 0.615, indicating that approximately 61.5% of the variance in green supply chain practices is explained by the predictor variables included in the model, while the remaining variance is attributable to factors not captured in this study. In comparison, the Sustainable Economic Efficiency construct exhibits a higher SMC value of 0.834, implying that 83.4% of its variance is accounted for by the model.

Overall, these results demonstrate that the proposed model possesses strong explanatory power, particularly with respect to sustainable economic efficiency. The explanatory capacity for the green supply chain construct is also substantial, falling within the moderate-to-strong range. This indicates that the integration of AI and green supply chain practices provides a robust framework for explaining variations in sustainable economic efficiency.

The empirical findings provide strong evidence regarding the role of artificial intelligence (AI) and green supply chain (GSC) practices in enhancing sustainable economic efficiency. Overall, the results support the proposed theoretical framework, which positions AI as a strategic enabler of green supply chain practices and sustainable economic outcomes (Table 5).

4.1. Artificial Intelligence and Green Supply Chain

The results indicate that Artificial Intelligence has a strong positive and significant effect on green supply chain practices (β = 0.765), suggesting that AI capabilities play a pivotal role in facilitating environmentally oriented supply chain activities. This finding is consistent with prior studies that emphasize the role of advanced digital technologies in improving green supply chain implementation. For example, Chen et al. (2024) and Que et al. (2024). Report that AI driven analytics and optimization tools enhance the effectiveness of GSCM by improving information accuracy, real time coordination, and resource utilization. Similarly, Teixeira et al. (2025) highlight that AI supported digital twins and predictive systems enable firms to proactively manage environmental risks across supply chain operations.

Table 5: SEM analysis

Variable	Estimate	Standard error	Critical ratio	P-value	Label
Artificial intelligence→Green supply chain	0.765	0.055	13.984	***	par_13
Green supply chain→Sustainable economic efficiency	0.563	0.058	9.670	***	par_14
Artificial intelligence→Sustainable economic efficiency	0.210	0.047	4.517	***	par_15

However, the magnitude of the relationship observed in this study is relatively stronger than that reported in several previous studies conducted in developed economies. This difference may reflect the context of an emerging economy, where AI adoption represents a more substantial shift from conventional practices, thereby generating larger marginal improvements in green supply chain implementation. In contrast, studies in technologically mature contexts often report more moderate effects, possibly due to diminishing returns from incremental digitalization.

From a theoretical perspective, this result is consistent with the resource based view (RBV) and the natural resource based view (NRBV), which argue that advanced technological capabilities constitute strategic resources that enable firms to develop superior environmental practices. AI enhances information accuracy, reduces uncertainty, and supports proactive decision-making, thereby facilitating the effective execution of Green Supply Chain initiatives. The strong magnitude of this relationship suggests that AI plays a central role in transforming sustainability objectives into operational practices, particularly in emerging economy contexts such as Indonesia.

4.2. Green Supply Chain and Sustainable Economic Efficiency

The finding that green supply chain practices positively affect sustainable economic efficiency (β = 0.563) aligns closely with the existing literature linking environmentally responsible supply chain practices to improved economic outcomes. Prior empirical research by Zhu et al. (2008) similarly demonstrates that GSCM contributes to cost reductions, improved operational efficiency, and enhanced firm performance. More recent studies within ASEAN contexts also confirm that green supply chain initiatives lead to simultaneous economic and environmental benefits Nguyen and Bui (2023) and Tran and Le (2023).

Nevertheless, some earlier studies report mixed or weaker economic effects of GSCM, particularly in contexts where environmental initiatives are perceived primarily as compliance driven rather than efficiency oriented. The relatively strong effect observed in this study suggests that when GSCM is supported by AI enabled capabilities, environmental practices are more likely to generate tangible economic efficiency gains. This finding contrasts with earlier arguments that green practices may impose additional costs, at least in the short term, and highlights the role of digital technologies in overcoming this trade-off.

This finding supports the triple bottom line (TBL) framework, which emphasizes the alignment of environmental responsibility with economic performance. Green supply chain practices contribute to sustainable economic efficiency by lowering energy consumption, reducing waste, minimizing emissions, and improving resource productivity. These efficiency gains translate into cost savings and improved operational performance, thereby reinforcing the economic rationale for sustainability oriented supply chain strategies.

4.3. Direct Effect of Artificial Intelligence on Sustainable Economic Efficiency

The analysis also reveals a positive and significant direct effect of AI on sustainable economic efficiency (β = 0.210), which is in agreement with studies emphasizing AI's role in improving productivity and operational efficiency. For instance, Chen et al. (2024) and Li et al. (2024) find that AI adoption enhances forecasting accuracy, reduces operational costs, and improves decision-making quality, leading to better performance outcomes.

However, the relatively smaller magnitude of the direct effect compared to the indirect effect through green supply chain practices highlights an important distinction from some technology-focused studies that emphasize AI as a standalone driver of performance. In contrast to such studies, the present findings suggest that AI delivers greater economic benefits when embedded within structured green supply chain practices. This result refines existing evidence by demonstrating that AI's contribution to sustainable economic efficiency is largely contingent on complementary organizational and environmental practices, rather than technological adoption alone.

These results have important implications for both theory and practice. Theoretically, they extend RBV and NRBV by demonstrating how AI enabled capabilities support the development of green supply chain practices that drive sustainable economic efficiency. Practically, the findings suggest that firms and policymakers should prioritize integrated strategies that combine AI adoption with green supply chain initiatives to maximize efficiency gains and sustainability outcomes.

5. CONCLUSION AND RECOMMENDATIONS

The empirical results demonstrate that AI significantly strengthens the implementation of GSC practices and contributes positively to sustainable economic efficiency. Notably, the findings indicate that the economic benefits of AI adoption are more pronounced when AI is integrated into environmentally oriented supply chain practices rather than applied in isolation.

From a theoretical perspective, this study extends the resource based view and the natural resource based view by empirically illustrating how AI enabled capabilities function as strategic resources that facilitate green supply chain practices and generate sustainable economic outcomes. By explicitly linking AI adoption, GSC practices, and sustainable economic efficiency, the study provides a more comprehensive understanding of how digital technologies can support the alignment of economic and environmental objectives.

From a managerial and policy standpoint, the results suggest that firms should prioritize the strategic integration of AI within their green supply chain initiatives to maximize efficiency gains and sustainability performance. Policymakers may also leverage these insights to design incentives and regulatory frameworks that encourage the adoption of AI-driven green practices as a means of promoting sustainable economic development, particularly in emerging economies.

Despite its contributions, this study has several limitations that should be acknowledged. First, the research relies on cross-sectional survey data, which limits the ability to infer causal relationships over time. Although the structural model provides evidence of significant associations, longitudinal data would allow for a more robust examination of dynamic effects and temporal causality.

Second, the measurement of AI adoption and green supply chain practices is based on self reported perceptions of respondents, which may introduce common method bias or subjective evaluation. While established measurement scales and statistical tests were employed to mitigate this concern, future studies could incorporate objective indicators or secondary data to enhance measurement accuracy.

Third, the study focuses on firms operating in Indonesia, which may limit the generalizability of the findings to other institutional and economic contexts. Differences in regulatory environments, technological infrastructure, and market maturity may influence the strength and direction of the observed relationships.

REFERENCES

AbdEllatif, M., Baazeem, T.A. (2025), Artificial intelligence adoption and supply chain efficiency: Evidence from emerging economies. International Journal of Production Economics, 262, 108926.

Ali, A., Zhang, L., Khan, S.A.R. (2024), Big data analytics and artificial intelligence for sustainable logistics and carbon emission reduction. Transportation Research Part E Logistics and Transportation Review, 181, 103360.

Barney, J. (1991), Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99-120.

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.

Chen, Y., Zhang, H., Yan, X., & Miao, Q. (2025), Supply chain demand forecasting based on multi-time scale data fusion network. Computers & Industrial Engineering, 207, 111324 .

Chen, X., Wang, Y., Liu, Z. (2024), Artificial intelligence-enabled logistics optimization for green supply chain management. International Journal of Production Economics, 259, 108795.

Dwidienawati, D., Abdinagoro, S.B., Tjahjana, D. (2025), Digital transformation, green supply chain, and firm efficiency: Evidence from Indonesia. Sustainability, 17(4), 1982.

Elkington, J. (1997), Cannibals with Forks: The Triple Bottom Line of 21st Century Business. England: Capstone Publishing.

High-Level Expert Group on AI, European Commission. (2018), A Definition of Artificial Intelligence: Main Capabilities and Scientific Disciplines. Belgium: European Commission.

Lai, K.H. (2008), Linking green logistics performance with environmental protection and competitiveness. Journal of Business Logistics, 29(1), 181-205.

Lee, M., Trimi, S. (2024), Innovation for creating a smart future: Artificial intelligence and business transformation. Journal of Business Research, 170, 114256.

Li, Y., Sun, H., Chen, J. (2024), Generative artificial intelligence and sustainable supply chain performance. Technological Forecasting and Social Change, 198, 122938.

Nguyen, T.H., Bui, H.M. (2023), Digitalization, green supply chain practices, and firm performance: Evidence from ASEAN countries. Asia Pacific Journal of Management, 40(3), 1121-1146.

OECD. (2011), Towards Green Growth. Paris: OECD Publishing.

Pham, T.N., Dao, H.T. (2023), Digital transformation and green supply chain management in emerging economies. Journal of Cleaner Production, 385, 135682.

Qu, Y., Liu, Y., Chen, J. (2024), Artificial intelligence applications in green supply chain management: A systematic literature review. Journal of Cleaner Production, 402, 136752.

Russell, S.J., Norvig, P. (2021), Artificial Intelligence: A Modern Approach. 4th ed. London: Pearson.

Sammut, C., Webb, G.I., editors. (2017), Encyclopedia of Machine Learning and Data Mining. 2nd ed. Berlin: Springer.

Seuring, S., Müller, M. (2008), From a literature review to a conceptual framework for sustainable supply chain management. Journal of Cleaner Production, 16(15), 1699-1710.

Srivastava, S.K. (2007), Green supply-chain management: A state-of-the-art literature review. International Journal of Management Reviews, 9(1), 53-80.

Shrivastava, P., Hart, S. (1995), Creating sustainable corporations . Business strategy and the environment, 4(3), 154-165.

Teixeira, A.A., Lopes, I., Faria, J. (2025), Digital twins and artificial intelligence for sustainable supply chain optimization. Computers Industrial Engineering, 189, 109844.

Toderas, M. (2025), Artificial intelligence for sustainability: A systematic review of applications and outcomes. Sustainable Development, 33(1), 45-62.

Tran, Q.T., Le, D.M. (2023), Green supply chain management and economic performance: The moderating role of digital capability. Sustainability, 15(9), 7521.

Wamba-Taguimdje, S.L., Wamba, S.F., Kamdjoug, J.R.K., Tchatchouang Wanko, C.E. (2020), Influence of artificial intelligence on firm performance: The business value of AI-based transformation projects. Business Process Management Journal, 26(7), 1893-1924.

World Business Council for Sustainable Development (WBCSD). (2000), Eco-Efficiency: Creating More Value with Less Impact. Bengal: WBCSD.

World Commission on Environment and Development (WCED). (1987), Our Common Future. Oxford: Oxford University Press.

Zhu, Q., Sarkis, J. (2008), Relationships between operational practices and performance among early adopters of green supply chain management practices in Chinese manufacturing enterprises. Journal of Operations Management, 26(3), 384-403.