**Communication in Physical Sciences, 2024 11(4): 1099-1111**

# A Review on machine learning and Artificial Intelligence in procurement: building resilient supply chains for climate and economic priorities

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**Received: 17 August 2024/Accepted: 18 October 2024/Published: 31 December 2024**

***Abstract:*** *With global supply chain facing unprecedented disruption from climate change and economic uncertainty driving a shift in procurement strategies from previously cost-focused decision-making toward sustainability and resilience, this review examines how Artificial Intelligence (AI) and Machine Learning (ML) can provide transformative solutions for building robust and adaptive supply chains that align with both climate and economic priorities. It discusses other key applications like automated sourcing solutions and contract administration, supplier selection model, multi-tier risk assessment with intelligent scoring models, demand forecasting and inventory optimization with predictive analytics. This paper also discusses the work of AI/ML in enhancing traceability and visibility, the application of digital twins and the circular economy to procurement to actively manage disruptions. The results indicate that the application of technology is significant in respect to cost effectiveness as opposed to corporate climate objectives, carbon reduction and environmental and social governance (ESG). Nevertheless, to effectively operationalize AI/ML, the resultant implementation-level challenges, such as human oversight, model explainability, and data quality, must be surmounted.*

***Keywords****: Artificial intelligence, Machine Learning, risk management, climate change, digital twins.*

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## 1. 0 Introduction

Machine Learning (ML) and Artificial Intelligence (AI) are transforming interdisciplinary fields through efficient systems for accurate data interpretation, predictive analytics, and autonomous operations (Ademilua, 2021; Adeyemi, 2023). Their integration facilitates innovative methods for real-time analysis and automated decision-making across sectors (Ufomba & Ndibe, 2023). AI and ML reshape research by processing large datasets and enhancing autonomous performance (Ndibe, 2024). The widespread adoption of these tools supports intelligent frameworks that strengthen analytical precision and operational efficiency (Ademilua & Areghan, 2022). By enabling intelligent automation and data-driven reasoning, they offer transformative solutions to modern challenges (Dada *et al*., 2024). Their applications improve data modelling, decision-making, and smart navigation (Okolo, 2023). Advanced techniques enhance computational intelligence and predictive modelling (Abolade, 2023), while their convergence optimizes real-time operations and dataset management (Utomi *et al*., 2024; Adeyemi, 2024). Overall, AI and ML redefine automation, analytical accuracy, and intelligent system design (Omefe *et al*., 2021).

The dual challenge of economic instability and climate-linked disruptions have become more evident in the global supply chain environment and requires significant and immediate system clearance. According to the most recent risk assessment report from the World Economic Forum, climate-related disasters, political instability and other economic shocks continue to feature high on the list of worst business continuity-risk threats (World Economic Forum, 2024). The compounding of basic dangers in these situations is dependent on the region and industries wherein local climate events have far-reaching consequences. Here, the term of the viability of the supply chain and the capacity of its networks to adjust, survive and thrive in the face of long-term changes has become typical (Ivanov & Dolgui, 2020; Ivanov, 2021). Questioning empirically based frameworks, views resilience as dynamic adaptability rather than robustness or redundancy to ensure performance and value in times of stress (Christopher and Holweg, 2017).

In practice, procurement could operationalize resilience and climate objectives by implementing supplier risk sensing, multi-sourcing and nearshoring strategies and considering sustainability criteria in category strategies and award decisions while holding cost in check (Ivanov, 2021; World Economic Forum, 2024). Against this backdrop, procurement has emerged as a major lever for both resilience and sustainability as it has impacts on supplier portfolios, contracting terms, inventory positioning, risk transfer and - crucially - emissions that are embedded in purchased goods and services. Supplier engagement requirements embedded in: science-based target setting is a further signpost to procurement role - companies with material scope 3 footprints are therefore expected to cover at least 67% of their scope3 risk emissions with supplier engagement and/or reduction targets - codifying procurement as a governance mechanism for decarbonization (Ivanov & Dolgui, 2020).

Machine learning (ML) and artificial intelligence (AI) are game-changing enablers to support this procurement-led agenda within any organization because they enhance the capability to sense, predict and optimize in the face of uncertainty. Systematic reviews highlight that rapid progress continues to be made in applying ML to supply chain risk management, from demand forecasting and lead time prediction to disruption detection and risk disruption mitigation decision support systems, but also highlight gaps in integrating risk ID /assessment and response end to end (Yang *et al.*, 2023). In purchasing and supply management in particular, recent mixed-methods evidence has been able to develop a map of concrete use-cases of such AI/ML solutions in purchasing (e.g., supplier-discovery and qualification, estimation of sustainability performance, cost analytics, negotiation support), and the detection of contract flexibility and risk (e.g., a supplier's retrenchment fee). Beyond procurement processes, the application of optimization through AI is demonstrably seen to minimize the logistical fuel use and emission levels thanks to the optimization of both routes and operations choices that come with dual benefits (Reuters, 2024). When combined with digital supply-chain twins and streaming IoT signals, AI adds to better real-time visibility - and "what-if" scenarios - that are at the heart of viability-oriented design (Ivanov, 2020; Yang *et al.*, 2023).

The aim here is the development of a procurement-centric framework for operationalizing ML/AI for resilient supply chains under climate and economic volatility. In doing this, it bridges the documented implementation gaps by the translation of academic advances in ML-driven risk management and digital twins to procurement practices as per the emerging target-setting and disclosure compliance norms (Yang *et al.*, 2023; Ivanov, 2021; Spreitzenbarth *et al.*, 2024).

## 2. 0 AI and ML applications in procurement

### *2.1 Predictive analytics for demand forecasting and inventory optimization*

Predictive analytics using machine learning (ML) and deep learning (DL) technology has become a cornerstone for demand forecasting and inventory optimization today (Fig 1). Recent reviews and empirical studies indicate that the ML models (random forests, gradient boosting, LSTM, CNN-LSTM hybrid models and transformer variants) have consistently outperformed traditional statistical approaches - especially for intermittent, multivariate, or exogenous signals in demand (e.g., promotions, weather and events) (Douaioui *et al*., 2024; Goel, 2024). The use of these models increases the accuracy of forecasts (lowers MAPE), decreases the need for safety stocks and increases inventory turns, thereby freeing up working capital and mitigating the risk of stock-outs (Douaioui *et al*., 2024; Modgil *et al*., 2022). The architecture for implementing these models typically involves a pipeline of data layers (ingestion; preprocessing, product cleaning; feature engineering; model training; explainability), and best practice case studies demonstrate how crucial combining ML forecasts with business rules and human oversight can be to prevent an excessive reliance on opaque models (Yang *et al*, 2023; Douaioui *et al*., 2024). In short, the use of predictive analytics enables procurement teams to shift from reactive replenishment practices to becoming strategic in buying , crucial to resiliency in the face of climate- and market-induced demand shocks (Yang *et al*., 2023; Modgil *et al*., 2022).

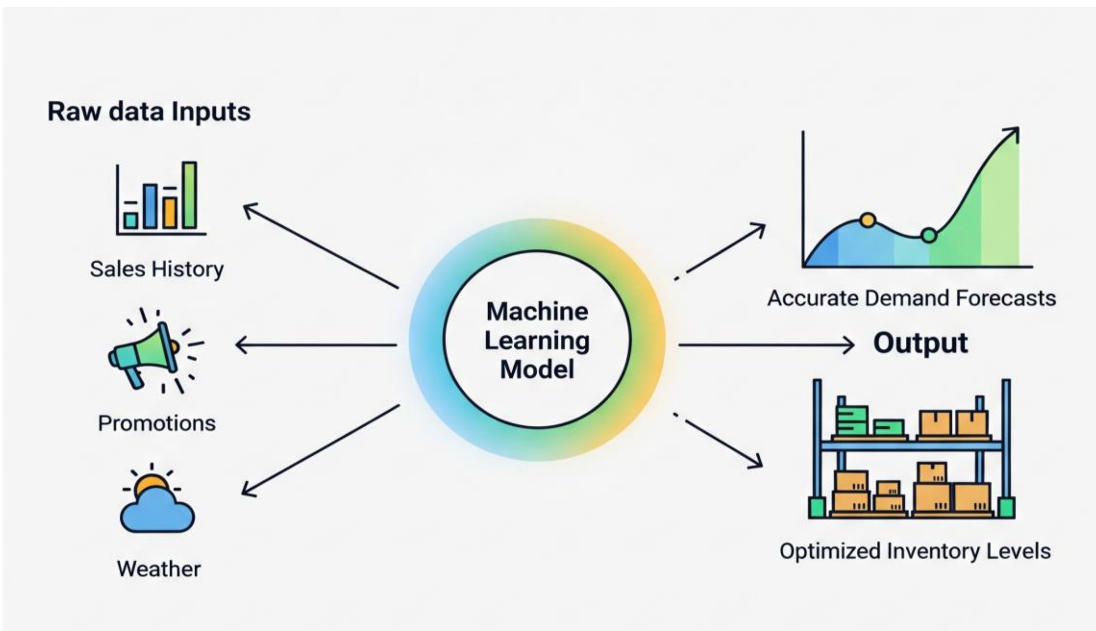


**Fig 1: Predictive analytics for demand forecasting and inventory optimization**

### *2.2 Supplier selection and risk assessment through intelligent scoring models*

Supplier selection and multi-tier risk assessment have been significantly improved using AI approaches that aggregate structured ERP/spend data sources with unstructured sources (news, social media and audit reports, financial filings) into composite risk and performance risk scores. Quantitative supplier scoring systems are based on supervised learning (classification/regression), ensemble methods, or Bayesian network for supplier default prediction, quality incidents/incident prediction, or delivery failure while unsupervised learning identifies unusual behavior in invoice patterns and delivery lead times (Yang *et al*, 2023). Research in food supply chains and manufacturing has found that AI-based scoring is effective for early identification of supply risks (contamination, logistics bottlenecks), as well as food safety and sustainability compliance (safety regulation versus environmental issues; ESG regulation versus food safety and traceability), with the potential to improve food system sustainability (Toorajipour *et al*., 2021). Crucially, research points to the need for quality of labels and data governance, cross-functional validation (legal, quality, and procurement) to ensure that scores are useful and that they don't discriminate against low-data regions and small suppliers (Spreitzenbarth *et al*. 2024; Yang *et al*. 2023).

### *2.3 Automation in sourcing, contract management, and spend analysis*

Automation backed by rule-based bots, natural language processing (NLP), and more generative artificial intelligence (AI) has led to excellence in contract-lifecycle management (CLM), reducing the length of their sourcing processes, and making expenditure analytics more granular and instant (Fig 2). Robotic process automation (RPA) coupled with machine learning (ML) for component supplier on-/offboarding, three-way reconciliation and invoice-PO matching, NLP models for clauses extraction, flagging risky clauses and clause-level benchmarking between contract pools (Spreitzenbarth *et al*., 2024; Toorajipour *et al*., 2021). With the combination of automation and appropriate change management and legal monitoring, studies and industry reports have shown measurable productivity benefits (time saving in RFX processing, accelerated contract review, higher contract compliance) (Spreitzenbarth *et al*. 2024; Modgil *et al*. 2022). Yet a number of empirical measures provide key warnings about "false confidence" given by automated scoring of a system or flags for clauses and human review for still novel or high risk contracts (Douaioui *et al*., 2024; Spreitzenbarth *et al*., 2024).


**Fig 2: Automation in sourcing, contract management, and spend analysis**

### *2.4 Case examples of AI/ML in global procurement practices*

An increasing number of documented cases demonstrate practical procurement deployments. Across various industries, manufacturing, and retail, several case studies of end-to-end implementation of AI technologies include retailers using ML-driven demand signals and aligning their replenishment and promotions with their demand, which includes CLM platforms and NLP to reduce the time needed for negotiations and increase compliance (Cannas, 2024). Manufacturers using AI for supplier risk monitoring and predictive maintenance procurement, and, Large buyers using CLM platforms to reduce the time needed for negotiations and increase compliance (Modgil *et al*, 2022). Based on the systematic reviews of spend-analysis causes in purchasing and supply management, 11 common use-case clusters are identified (use-cases of supplier scoring, demand forecasting, spend-analysis, CLM, sourcing optimization and fraud/anomaly detection, etc.) and that, despite the diversity of opportunities, mature, wide-scale adoption versions are still limited to early adopters with strong data grounds and cross-functional teams. Also, empirical insights suggest digital twins and the integration of IoT architectures could be the impetus for operationalizing A.I.S. At scale, digital twins allow for the scenario-based "what-if" testing for sourcing decisions under weather, transport, and demand shocks, making them particularly pertinent for climate-sensitive procurement strategies (Yang *et al*., 2023. Collectively, these cases/reviews demonstrate that AI/ML has the potential to materially enhance the role of procurement in the applied policy of resilience and sustainability, if organizations invest in efforts of data quality, data governance, model explainability, and human-in-the-loop processes (Spreitzenbarth *et al*., 2024; Modgil *et al*., 2022; Douaioui *et al*., 2024).

## 3. 0 Building resilient supply chains

### *3.1 Enhancing visibility and traceability across procurement networks*

Visibility and traceability are needed to have resilient procurement networks. Full transparency - knowing who's providing what, when, and where - is an organization's "eyes and ears" which can enable early warning of shocks such as a factory shutting down, logistic delays, or supplier insolvency. Further academic studies show that traceability reduces information asymmetry, facilitates regulatory adherence for environmental and social compliance standards, and enhances surveillance for multi-tier supply chain risk (Budler *et al*., 2024). Implementations combining ERP/spend systems, EDI transaction logs, IoT telemetry (think IoT-enabled pallets, GPS-tracked shipments), and unstructured external data sources (new, trade alerts, sanctions lists) help us increase visibility into upstream supply chains and identify previously hidden dependencies (Ivanov & Dolgui, 2020; Longo *et al*., 2023). Furthermore, AI-powered entity resolution and provenance tracking may reconstruct material journeys on multiple tiers - even those that reach into small or far-flung suppliers - so that procurement teams can carry out scenarios-based stress tests, alternate sourcing analyses and supply shock response planning, particularly for climate-sensitive or conflict-prone regions (Ivanov 2021; Budler 2024). By digitizing and harmonizing data as well as connecting it with supplier metadata, for example, certifications, or ESG performance-organizations will have the insight needed to respond quickly to pivot to rivals with long-lived alternatives as signals of disruption arrive.

### *3.2 Risk prediction and disruption management*

Effective disruption management needs both visibility and anticipatory intelligence. In order to make an estimate of the risk of disruption and the resulting impact on lead times, costs and service levels, recent studies have shown that machine learning models, for example ensemble tree methods, recurrent networks, and hybrid architectures that incorporate physics-based constraints can consume and interpret various inputs, including weather forecasts, shipping congestion, commodity price shocks, geopolitical news, and financial health indicators (Yang *et al*., 2023; Modgil *et al*., 2022). Procurement leaders can use these models to identify suppliers and sourcing lanes that will be at risk of major delays or cost overruns. Furthermore, planners can explore what-if scenarios with a process known as scenario planning, which is enabled by the use of digital twins or simulation platforms. For instance, how would the supply chain suffer in the event of severe weather, an abrupt export embargo or a shortage of minerals. Decision-makers can evaluate mitigation measures, for example, buffer stock by exploring dual sourcing, and understand the cost trade-offs in different scenarios using the help of these analyses (Ivanov & Dolgui, 2020; Longo *et al*., 2023). However, the literature does warn that for this predictive forecasting to avoid paralysing organizations or misallocating limited emergency resources, predictive forecasts are required to be embedded into explicit decision-making guidelines, such as automated escalation rules or threshold triggers (Spreitzenbarth *et al*., 2024; Yang *et al*., 2023). Risk prediction, if done right, transforms procurement from firefighter to resilience orchestrator.

### *3.3 Integration of circular economy principles and green procurement using AI/ML insights*

Using the principles of the circular economy - reuse, repair and remanufacture - in your procurement means that dependency on new resources are kept to a minimum and vulnerability to commodity volatility is reduced, thus building resilience. Reverse-logistics routing optimization can reduce the cost-to-serve for refurbishments, computer vision and/or spectrometry models can examine returned products and assess their salvage value or reusability, and prescriptive machine learning algorithms can determine under which conditions it's less costly to refurbish an item instead of purchasing a new one (Sjödin *et al*., 2023). AI/ML is crucial to the implementation of circular procurement. In particular, failure probability and residual value models would be useful in making decisions involving vendor take-back schemes or trade-in schemes, to maintain supply continuity and smoothly sustain sustainability efforts. To achieve circular procurement lift-off, it requires institutional solutions like the siloed nature of data, or conflicting KPIs/regulation to be addressed, as reported by empirical research, which means that these circular approaches (in anaerobic form) need to be integrated systems to merge procurement and operations data with sustainability data (Sjödin *et al*., 2023; Nasir *et al*., 2017). Beyond this, procurement can be explicit about trade-offs by incorporating circularity measures (including reuse rates, lifecycle emissions and material intensity) into various aspects of scored suppliers, or sourcing optimization, for AI applications. This allows procurement to select suppliers/policies to reduce raw material risk through decarbonization arrangements (Spreitzenbarth *et al*. 2024; Sjödin *et al*. 2023). By utilizing circular procurement design, AI/ML is essentially helping firms operationalize sustainability and resilience together.

### *3.4 Collaborative platforms and digital twins for scenario modelling and resilience testing*

Collaborative platforms with digital twins improve resilience by providing supply chain participants - including buyers, suppliers, transporters, insurers and regulators - with the tools to model scenarios collaboratively. Digital twins combine real-time data (e.g., sensor feeds, transactional data) with engines for business simulations to re-create behaviour in supply chains and run many alternatives in order to intervene: re-routing, dual sourcing, repositioning of stock, or modes of transportation. Planners can consider operational performance measures such as recovery time objectives (RTO) and cost to mitigate in the context of climate events and/or cyber intrusion (Longo *et al*., 2023; Ivanov, 2021). Additional degrees of resiliency are built when these platforms are coupled with other technological capabilities such as blockchain (for immutable traceability logs) or federated learning (for privacy-preserving AI training across organizations), enabling collaborative learning in a manner which maintains confidentiality for the parties involved, allowing stakeholders to share their insights and co-optimize the resiliency of the supply chain, and retain confidentiality of their data (Liu *et al*., 2024; Spreitzenbarth *et al*., 2024). Some researchers have demonstrated in case studies that collaborative architectures can involve recovery time minimization, cost-efficiency of mitigation strategies, and trust-building across supply chain ecosystems - but it's only if organizations pay for shared data standards, access governance, and cross-organisation capabilities (Longo *et al*., 2023; Ivanov & Dolgui, 2020). Ultimately, resilient supply chains of the future will be the socio-technical ecosystem, with the convergence of AI-augmented visibility and scenario modelling, circular procurement, and collaborative governance for agility and sustainability. Fig. 3 shows the various applications in building Resilient Supply Chains.

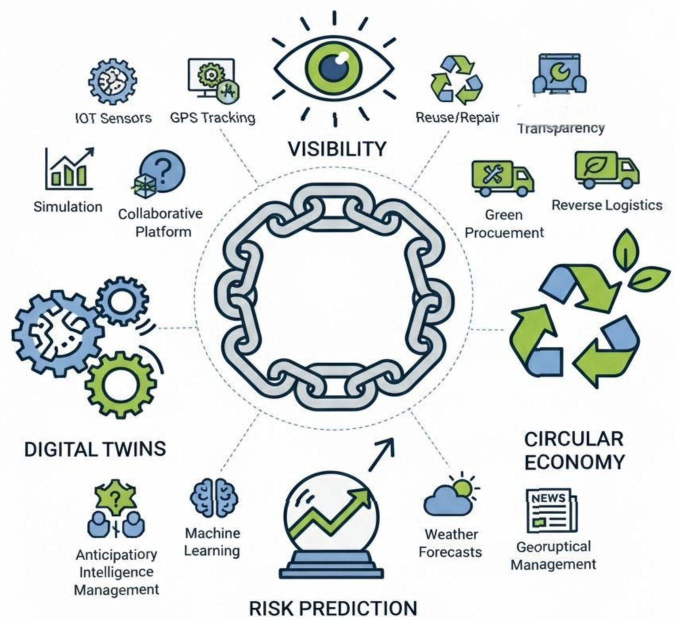


**Fig 3: Different applications in building resilient supply chains**

## 4.0 Climate and economic priorities in procurement

### *4.1 Leveraging AI/ML for sustainable sourcing and carbon footprint reduction*

AI (Artificial Intelligence) and ML (Machine Learning) are changing the way procurement is viewed from sustainable practices to a sustainable-minded function by creating data-driven approaches for sourcing goods and managing emissions (Fig. 4). AI/ML models enable buyers to monitor emissions throughout their supply chain, measure their suppliers' sustainability performance and determine where they can lower their carbon footprint (Tsolakis *et al*, 2021). Predictive analytics can be of assistance in this regard, by modeling the lifecycle carbon cost and weighing on suppliers that resonate with low emissions targets (Jia *et al*., 2018). Similarly, AI-based optimization will allow organisations to shift logistics routes and transport mode to curb carbon emissions (Tsolakis *et al*, 2021). These applications fulfil many goals of corporate progress towards sustainability as procurement in some industries is responsible for 80% of the organisations total carbon footprint (Raman *et al*., 2023). Furthermore, ML-powered sustainability dashboards can enable carbon intensity to be monitored between suppliers and across geography for procurement groups and to meet international climate disclosure frameworks (Naz *et al*., 2022). These are ways to reduce emissions today, but also make the process attractive for any new carbon pricing regimes. By upgrading sourcing decisions with AI and ML, companies can operationalize their climate commitments while balancing the amount of spending and expected level of efficiency.

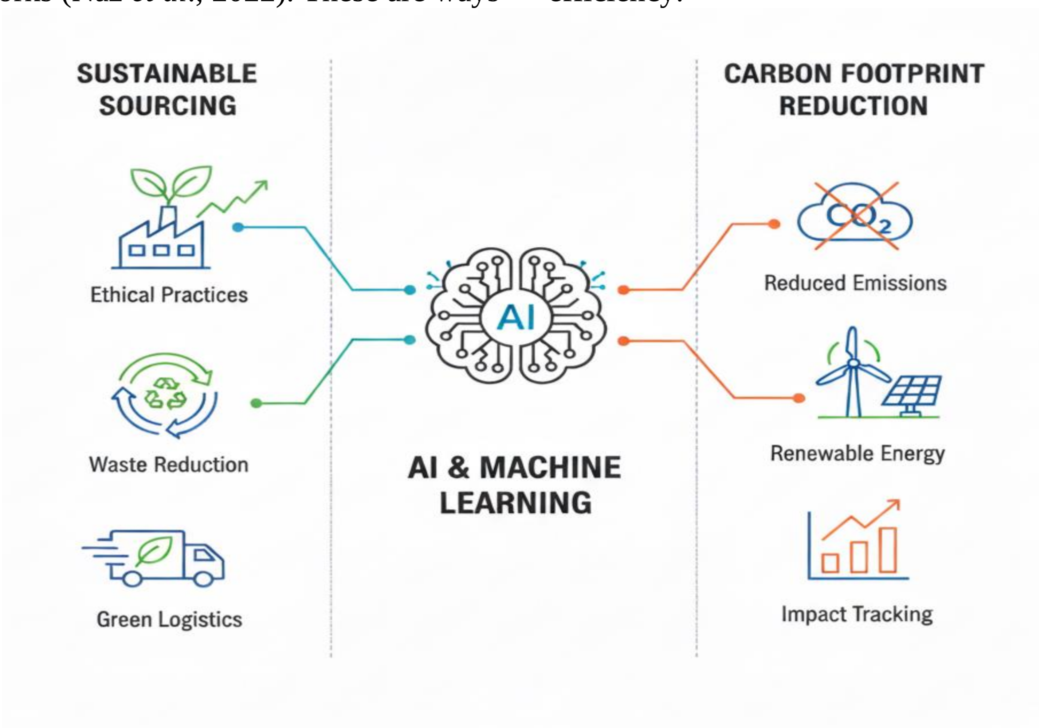


**Fig 4: Leveraging AI/ML for sustainable sourcing and carbon footprint reduction**

### *4.2 Balancing cost efficiency with environmental and social governance (ESG) goals*

Cost-driven procurement has been the norm in the past, and companies are now looking to balance cost -effectiveness and the firm's respective sustainability priorities because of growing goblin pressure (Kumar *et al*, 2012). The AI and ML technologies help the organization to make a "trade-off" between being well-priced, in line to ESG on the side's large volumes of data from suppliers (Kraljic, 1983) (Fig 5). As an example, AI-based supplier scoring models would be able to assess ESG-related standards, behaviours, ethics, and pollution in the context of decision-making (Rajesh, 2020). The analysis of scenario planning to determine e.g., the effect of on ESG investments on cost efficiency can be done with predictive ML models (Queiroz *et al*., 2022). These features allow procurement managers to apply a dual lens 5 approach to reviewing not only cost-effectiveness, but also social value in supplier optimization. This is important in light of the increasingly widespread recognition of the reality that ESG factors do not solely represent a compliance tool, but also r represent an engine in already generating long-term value and in managing risk in all forms of business (Eccles and Klimenko, 2019). Incorporating AI and ML in the ESG procurement processes will allow businesses to come closer to a systemic model where the destiny of sustainability and financial performance is bound together.


**Fig 5: The striking a balance between cost efficiency and environmental and social governance goals.**

***4.3 Contribution to global climate targets and corporate sustainability reporting***

Climate targets such as those established by the Paris Agreement have made it imperative that firms implement climate targets as reported by leaning on decreasing the carbon footprint and reducing the emissions caused by value chain operations (UNFCCC, 2015). This is particularly relevant in the category of procurement, given the scale of relevance of supply chain emissions, which in some industries can be much larger than direct operations (Raman *et al*., 2022). AI and ML will further enhance corporate capacities aligned with these global commitments because they will provide transparency and will support the automation of Scope 3 emission reporting (Chehrehgosha Kenari, 2022). It is possible to use natural language processing (NLP) and automated data collection technologies on sustainability reporting to ensure that reporting complies with reporting rules, such as the Task Force on Climate - Linked Financial Disclosures (TCFD) and the Global Reporting Initiative (GRI) (Eccles *et al*. 2020). Moreover, this benchmarking can be employed by the machine learning models to ensure that the business procurement procedures are comparable to their counterparts in the market. They also have the capability to recognize cases of noncompliance and even prescribe remedial actions to achieve climate goals (George *et al*., 2021).

This heightens the business and trust liabilities of the stakeholders. Companies are encouraged to make their sustainability reporting endeavours more accurate and show their commitment to regulatory compliance through the use of AI/ML-based automation. AI-based procurement also provides companies with an opportunity to fulfi l more demanding global climate obligations, thus facilitating companies' achieving their climate objectives without compromising their market competitiveness.

**5.0 Conclusion**

This paper reveals the potential of Artificial Intelligence and Machine Learning (AI and ML) to radically improve the resilience and sustainability of procurement processes and supply chains. AI/ML solutions allow predictive risk management, automated spend management, and real-time disruption monitoring, which make procurement more responsive, visible and strategically focused on climate and economic priorities compared to conventional models. With data-driven insights, they can vastly enhance supply chain visibility, enhance the allocation of resources, and further Environmental and Social Governance (ESG) purposes. However, some of the difficulties associated with data quality, model interpretability, and ethical usage of algorithms require cautious use. Although AI / ML can simplify the screening of suppliers and emissions monitoring, their efficacy relies on the ability to address problems in the area of data management, human control, and organizational resistance to automated decision-making.

## 6.0 References

Ademilua, D. A., & Areghan, E. (2022). AI-Driven Cloud Security Frameworks: Techniques, Challenges, and Lessons from Case Studies. *Communication in Physical Sciences*, *8*, 4, pp. 674–688.

Ademilua, D.A. (2021). Cloud Security in the Era of Big Data and IoT: A Review of Emerging Risks and Protective Technologies. *Communication in Physical Sciences*, 7, 4, pp. 590-604

Adeyemi, D, S. (2023). Autonomous Response Systems in Cybersecurity: A Systematic Review of AI-Driven Automation Tools. *Communication in Physical Sciences*, 9, 4, pp. 878-898.

Adeyemi, D, S. (2024). Effectiveness of Machine Learning Models in Intrusion Detection Systems: A Systematic Review. *Communication in Physical Sciences*, 11, 4, pp. 1060-1088.

Abolade, Y.A. (2023). Bridging Mathematical Foundations and intelligent system: A statistical and machine learning approach. *Communications in Physical Sciences*, 9, 4, pp. 773-783

Dada, S.A, Azai, J.S, Umoren, J., Utomi, E., & Akonor, B.G. (2024). Strengthening U.S. healthcare Supply Chain Resilience Through Data-Driven Strategies to Ensure Consistent Access to Essential Medicines. *International Journal of Research Publications*, *164*, 1, https://doi.org/10.47119/IJRP1001641120257438

Budler, M., Quiroga, B. F., & Trkman, P. (2024). A review of supply chain transparency research: Antecedents, technologies, types, and outcomes. *Journal of Business Logistics*, 45, 1, e12368. https://doi.org/10.1111/jbl.12368.

Cannas, V. G. (2024). Artificial intelligence in supply chain and operations management: A multiple-case study research. International *Journal of Production Research*. https://doi.org/10.1080/00207543.2023.2232050

Chehrehgosha Kenari, A. (2024). The use of digital tools in Scope 3 emissions reporting (Master's thesis, A. Chehrehgosha Kenari). https://urn.fi/URN:NBN:fi:oulu-202405143463.

Christopher, M., & Holweg, M. (2017). Supply Chain 2.0 revisited: A framework for managing volatility-induced risk in the supply chain. *International Journal of Physical Distribution & Logistics Management*, 47(1), 2–17. https://doi.org/10.1108/IJPDLM-09-2016-0270

Douaioui, K., Oucheikh, R., Benmoussa, O., & Mabrouki, C. (2024). Machine learning and deep learning models for demand forecasting in supply chain management: A critical review. *Applied System Innovation*, 7, 5, 93. https://doi.org/10.3390/asi7050093

Eccles, R. G., & Klimenko, S. (2019). The investor revolution. Harvard Business

Review, 97, 3, pp. 106–116. https://hbr.org/2019/05/the-investor-revolution

Eccles, R. G., Krzus, M. P., & Solano, C. (2020). A comparative analysis of integrated reporting in ten countries. *Sustainability*, 12, 14, 5250. https://doi.org/10 z.3390/su12145250

George, G., Merrill, R. K., & Schillebeeckx, S. J. (2021). Digital sustainability and entrepreneurship: How digital innovations are helping tackle climate change and sustainable development. *Entrepreneurship Theory and Practice*, 46, 2, pp. 255–280. https://doi.org/10.1177/1042258719899425

Goel, L., Nandal, N., Gupta, S., Karanam, M., Prasanna Yeluri, L., Pandey, A. K., ... & Grabovy, P. (2024). Revealing the dynamics of demand forecasting in supply chain management: a holistic investigation. *Cogent engineering*, 11, 1, 2368104. https://doi.org/10.1080/23311916.2024.2368104.

Ivanov, D. (2021). Supply chain viability and the COVID-19 pandemic: A conceptual and formal generalisation of four major adaptation strategies. *International Journal of Production Research*, 59, 12, pp. 3535–3552. https://doi.org/10.1080/00207543.2021.1948261

Ivanov, D. (2022). Viable supply chain model: integrating agility, resilience and sustainability perspectives—lessons from and thinking beyond the COVID-19 pandemic. *Annals of operations research*, 319, 1, pp. 1411-1431. https://doi.org/10.1007/s10479-020-03640-6

Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. *International Journal of Production Research*, 58, 10, pp. 2904–2915. https://doi.org/10.1080/00207543.2020.1750727

Jia, F., Zuluaga-Cardona, L., Bailey, A., & Rueda, X. (2018). Sustainable supply chain management in developing countries: An analysis of the literature. *Journal of cleaner production*, 189, pp. 263-278. https://doi.org/10.1016/j.jclepro.2020.120655

Kumar, S., Teichman, S., & Timpernagel, T. (2012). A green supply chain is a requirement for profitability. *International Journal of Production Research*, 50, 5, pp. 1278-1296.

Longo, F., Mirabelli, G., Padovano, A., & Solina, V. (2023). The Digital Supply Chain Twin paradigm for enhancing resilience and sustainability against COVID-like crises. *Procedia Computer Science*, 217, pp. 1940–1947. https://doi.org/10.1016/j.procs.2022.12.394

Modgil, S., Singh, R. K., & Hannibal, C. (2022). Artificial intelligence for supply chain resilience: Learning from COVID-19. *International Journal of Logistics Management*, 33, 4, pp. 1246–1268. https://doi.org/10.1108/IJLM-02-2021-0094

Ndibe, O.S., Ufomba , P.O. (2024). A Review of Applying AI for Cybersecurity: Opportunities, Risks, and Mitigation Strategies. *Applied Sciences, Computing, and Energy*, 1, 1, pp. 140-156

Nasir, M. H. A., Genovese, A., Acquaye, A. A., Koh, S. C. L., & Yamoah, F. (2017). Comparing linear and circular supply chains: A case study from the construction industry. *International Journal of Production Economics*, 183, pp. 443-457. https://doi.org/10.1016/j.ijpe.2016.06.008.

Naz, F., Agrawal, R., Kumar, A., Gunasekaran, A., Majumdar, A., & Luthra, S. (2022). Reviewing the applications of artificial intelligence in sustainable supply chains: Exploring research propositions for future directions. *Business Strategy and the Environment*, 31, 5, pp. 2400-2423. https://doi. zorg/ z10.1002/bse.3034

Okolo, J. N. (2023). A Review of Machine and Deep Learning Approaches for Enhancing Cybersecurity and Privacy in the Internet of

Devices. *Communication in Physical Sciences*. 9, 4, pp. 754-772

Omefe, S., Lawal, S. A., Bello, S. F., Balogun, A. K., Taiwo, I., Ifiora, K. N. (2021). AI-Augmented Decision Support System for Sustainable Transportation and Supply Chain Management: A Review. *Communication In Physical Sciences*. 7, 4, pp. 630-642.

Queiroz, M. M., Ivanov, D., Dolgui, A., & Fosso Wamba, S. (2022). Impacts of epidemic outbreaks on supply chains: mapping a research agenda amid the COVID-19 pandemic through a structured literature review. *Annals of operations research*, 319, 1, pp. 159-1196. https://doi.org/10.1007/s10479-020-03685-7

Raman, R., Sreenivasan, A., Ma, S., Patwardhan, A., & Nedungadi, P. (2023). Green supply chain management research trends and linkages to UN sustainable development goals. *Sustainability*, 15, 22, 15848. https://doi.org/10.3390/su152215848

Rajesh, R. (2020). Exploring the sustainability performances of firms using supplier selection criteria. *Journal of Cleaner Production*, 250, 119581. https://doi.org/10.1016/j.jclepro.2019.119600

Reuters. (2024). AI can help shipping industry cut down emissions, report says. https://www.reuters.com/technology/artificial-intelligence/ai-can-help-shipping-industry-cut-down-emissions-report-says-2024-06-18/

Sjödin, D., Parida, V., & Kohtamäki, M. (2023). Artificial intelligence enabling circular business model innovation in digital servitization: Conceptualizing dynamic capabilities, AI capacities, business models and effects. *Technological Forecasting and Social Change*, 197, 122903.https://doi.org/10.1016/j.techfore.2023.122903.

Spreitzenbarth, J. M., Bode, C., & Stuckenschmidt, H. (2024). Artificial intelligence and machine learning in purchasing and supply management: A mixed-methods review of the state-of-the-art in literature and practice. *Journal of Purchasing and Supply Management*, 30, 1, 100829. https://doi.org/10.1016/j.pursup.2024.100829

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, 122, pp. 502-517. https://doi.org/10.1016/j.jbusres .2020.09.009

Tsolakis, N., Niedenzu, D., Simonetto, M., Dora, M., & Kumar, M. (2021). Supply network design to address United Nations Sustainable Development Goals: A case study of blockchain adoption. *Journal of Business Research*, 131, pp. 495–507. https://doi.org/10.1016/j.jbusres.2020.08.003

Ufomba , P.O., Ndibe, O. S. (2023). IoT & Network Security: Researching Network Intrusion and Security Challenges in Smart Devices. *Communication in Physical Sciences*. 9, 4, pp. 784-800

Utomi. E., Osifowokan, A. S., Donkor. A. A, & Yowetu. I. A. (2024). Evaluating the Impact of Data Protection Compliance on AI Development and Deployment in the U.S. Health sector. *World Journal of Advanced Research and Reviews*, 24, 2, pp. 1100–1110. https://doi.org/10.30574/wjarr.2024.24.2.3398

UNFCCC. (2015). The Paris Agreement. United Nations Framework Convention on Climate Change. https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement

World Economic Forum. (2024). Global Risks Report 2024. World Economic Forum. https://www.weforum.org/reports/global-risks-report-2024

Yang, M., Lim, M. K., Qu, Y., Ni, D., & Xiao, Z. (2023). Supply chain risk management with machine learning technology: A literature review and future research directions. *Computers & Industrial Engineering*, 175, 108859. https://doi.org/10.1016/j.cie.2022.108859

**Declaration**

**Consent for publication**

Not Applicable

**Availability of data and materials**

The publisher has the right to make the data public

**Ethical Considerations**

Not applicable

**Competing interest**

The author report no conflict or competing interest

**Funding**

No funding

**Authors' Contributions**

All components of the work were carried out by the author.