

AI-Driven Sustainable Procurement: Balancing Strategy and ESG Compliance



Yuliia Zorina

Global Sourcing, Global Leading Media Corporation,
Headquarters.

Author's Email:

julia.zorina14@gmail.com

Article's History

Submitted: 2nd November 2025

Revised: 16th November 2025

Published: 20th November 2025

Abstract

Aim: This study aims to evaluate the role of Artificial Intelligence (AI) in enhancing sustainable supplier assessment within ESG-focused procurement systems, ultimately demonstrating AI's potential as a transparent, adaptive, and scalable tool for sustainable supplier evaluation.

Methods: The research adopts a mixed-methods approach combining qualitative analysis of international ESG standards (GRI, ISO 20400), an algorithmic review of AI techniques (Machine Learning, Natural Language Processing, Explainable AI), and an in-depth case study of Unilever. The core procedure involved developing an analytical matrix to systematically compare traditional and ESG-oriented supplier selection and formulating a framework for embedding ESG-by-design principles into digital procurement platforms.

Results: Findings reveal that AI-enabled procurement systems significantly improve transparency, scalability, and adaptability in supplier ESG assessments compared to traditional methods. The analytical matrix highlights AI's superior predictive capabilities for risk mitigation, facilitating a shift from simple compliance checking to proactive risk management.

Conclusion: This work substantiates the need to combine AI tools with an ethical approach to supply chain management under conditions of uncertainty and risk, establishing ESG integration not just as an ethical imperative but a strategic necessity.

Recommendations: The main practical implication is the imperative for organizations to shift from reactive compliance to a proactive risk architecture, mandating the use of AI tools under strict ethical governance for reliable supply chain resilience. Strategic recommendations include embedding ESG criteria natively within digital procurement platforms and adopting the developed AI-driven classification matrix.

Keywords: *Artificial intelligence, sustainable procurement, digital platforms, ESG indicators, supplier classification matrix.*

INTRODUCTION

Against the backdrop of a global transformation of economic models driven by digitalization, escalating climate challenges, and growing corporate social responsibility, the procurement activities of organizations are undergoing substantial conceptual shifts. Modern supply chain management paradigms are increasingly aligning with the principles of sustainable development, which emphasize the harmonization of economic feasibility, environmental performance, and social equity. According to the Thomson Reuters Institute (2024), 81% of global trade professionals now consider ESG criteria important or very important in their supplier selection decisions, validating the shift toward value-driven sourcing models. Within this context, the integration of ESG (Environmental, Social, Governance) factors into strategic and operational decision-making processes is gaining prominence.

ESG criteria are gradually evolving from declarative benchmarks into full-fledged instruments for evaluating suppliers' compliance with sustainability requirements, becoming essential for companies operating in complex regulatory environments and focused on long-term value. Simultaneously, the need to account for cost, quality, risks, and ESG indicators imposes significant analytical burdens and necessitates the implementation of intelligent digital tools to support decision-making. Given the increasing complexity and multidimensionality of modern procurement strategies, traditional supplier selection approaches are insufficient for ensuring transparency, objectivity, and sustainability. In this context, artificial intelligence (AI) emerges not merely as a technological alternative but as a necessary component for the balanced operation of procurement systems within ESG frameworks.

Modern supply chain management paradigms are increasingly aligning with the principles of sustainable development, which emphasize the harmonization of economic feasibility, environmental performance, and social equity. To address the complexities inherent in monitoring these broad criteria and to manage increasing regulatory demands, the integration of AI technologies emerges as a critical necessity. AI technologies-particularly machine learning methods, natural language processing, and explainable analytics-unlock fundamentally new possibilities for automated, scalable, and adaptive supplier evaluation, taking into account complex ESG markers. Their application in sustainable procurement may catalyze transitioning from formal ESG oversight to dynamic responsibility management across supply chains. However, despite the increasing emphasis on ESG compliance, existing procurement models lack intelligent analytical frameworks that can integrate multi-dimensional sustainability indicators into supplier evaluation processes.

The core aim of this article is to develop a novel supplier classification matrix to systematically compare traditional and AI-enhanced ESG supplier selection methodologies, and to offer a concrete framework for integrating ESG-by-design principles into digital procurement platforms, thereby supporting data-driven decision-making in sustainable sourcing. This study contributes significantly to the literature by establishing a conceptual framework that tightly links AI-based decision models with ESG evaluation metrics, providing organizations with a structured pathway to operationalize sustainable procurement.

LITERATURE REVIEW

The emergence of sustainable procurement as an element of strategic supply management occurred amid increasing globalization, intensifying environmental challenges, and heightened social and regulatory expectations for corporate accountability. The methodological foundation for institutionalizing responsible sourcing principles is established by a number of internationally recognized regulatory documents and voluntary standards, which

systematically structure ESG (Environmental, Social, Governance) requirements in procurement activities.

Notably, ISO 20400:2017 Sustainable Procurement – Guidance provides a comprehensive framework for embedding sustainability principles into organizational procurement policies, considering aspects such as life cycle assessment, stakeholder impact, due diligence in supply chains, and the integration of non-financial risks into decision-making processes. ISO 20400 emphasizes the need for a cross-functional approach to procurement and alignment of supplier selection criteria with broader sustainability objectives.

The GRI Standards (Global Reporting Initiative) offer an additional structural framework for non-financial reporting, presenting unified approaches for disclosing environmental and social indicators in corporate reports. Within procurement contexts, the standards highlight parameters such as labor rights in supply chains, supplier impact on biodiversity, climate policies, resource use, and adherence to ethical governance practices. The GRI Standards (Global Reporting Initiative) offer an additional structural framework for non-financial reporting, presenting unified approaches for disclosing environmental and social indicators in corporate reports. Within procurement contexts, the standards highlight parameters such as labor rights in supply chains, supplier impact on biodiversity, climate policies, resource use, and adherence to ethical governance practices. While ISO 20400 provides a broad, voluntary framework for integrating sustainability into procurement operations, its non-prescriptive nature limits uniform adoption; conversely, GRI Standards offer measurable indicators but are often criticized for promoting mere box-ticking rather than driving transformative, end-to-end change. This clear distinction shows that although frameworks like the ISO 20400 and GRI Standards provide essential normative guidance on sustainable procurement, they fail to offer the analytical models or continuous, data-driven tools necessary to monitor complex, multi-dimensional supplier data in real-time. This critical implementation gap directly drives the need for AI-based approaches to operationalize ESG data for effective evaluation and decision-making.

The United Nations Sustainable Development Goals (UN SDGs) serve as a guiding political reference, with Goals 8 (Decent Work and Economic Growth), 12 (Responsible Consumption and Production), and 13 (Climate Action) being most relevant to procurement. Integrating SDGs into procurement practices necessitates a shift from transactional models toward multidimensional systems for evaluating the societal impact of procurement operations (Giudici & Wu, 2025).

Complementary to these is the OECD Due Diligence Guidance for Responsible Business Conduct, which outlines a sequence of actions for identifying, preventing, mitigating, and monitoring ESG-related risks across global value chains. Special attention is given to managing systemic risks arising from interactions with suppliers characterized by elevated environmental or social vulnerabilities. In the academic literature, ESG metrics are typologized as operationalized criteria for assessing supplier sustainability. Common examples include:

1. Environmental (E) encompass greenhouse gas emissions (GHG Scope 1–3), energy efficiency, water consumption, waste generation, environmental certifications;
2. Social (S) include labor rights compliance, union representation, occupational safety, inclusiveness, community impact;
3. Governance (G) entails anti-corruption policies, transparency in decision-making, corporate oversight structure, compliance procedures.

Despite the extensive theoretical groundwork, a notable gap remains between normative frameworks and their practical application in analytical decision-support systems, particularly concerning the role of AI technologies in delivering holistic ESG assessments. This research aims to address that gap (Abhayawansa & Tyagi, 2021). This study directly addresses that shortcoming by demonstrating how machine learning can bridge the data interpretation gap, offering a novel AI-driven supplier classification matrix for evidence-based ESG evaluation. To bridge the identified gap between normative ESG frameworks and their practical application, this study employs a methodology centered on machine learning algorithms capable of translating qualitative and quantitative ESG data into actionable supplier scores.

Recent studies and publications demonstrate growing scholarly interest in AI-ESG integration. For instance, Giudici & Wu (2025), Yu et al. (2025), and Xu (2024) emphasize AI's potential to enhance ESG assessment efficiency, data automation, and strategic planning in financial sectors. Abhayawansa & Tyagi (2021) highlight opacity in ESG ratings, which complicates investor use. Meanwhile, Fafaliou et al. (2022) explore the link between ESG reputation and firm longevity. Case-based publications on Unilever (Mirza, 2024; Oxford Executive, n. d.; Unilever, 2020) reflect both successes and challenges in implementing ESG strategies. Sydoryuk & Leschiy (2024) and Rane et al. (2024) stress the regulatory and technological barriers to AI deployment, while Segun-Ajao (2025) discusses its role in fostering sustainable supply chains. The ongoing scientific discourse thus seeks a balance between innovation, transparency, and accountability within ESG frameworks.

METHODOLOGY

The methodological framework of this study is grounded in a systems approach to modeling supplier evaluation processes that incorporate ESG parameters within the context of procurement digitalization. Specifically, the research adopts an exploratory quantitative design using proprietary secondary ESG datasets derived from corporate disclosures. This design is essential as it facilitates the robust comparative modeling and testing of AI algorithms for multi-criteria supplier evaluation based on complex ESG indicators. The core analytical toolkit involves typologizing machine learning and AI algorithms capable of automating the processing and interpretation of large-scale structured and unstructured data relevant to environmental, social, and governance criteria.

Specifically, classification and clustering algorithms (e.g. logistic regression, random forest, gradient boosting, and multilayer neural networks) have demonstrated high effectiveness in building ESG scoring models and ranking suppliers based on multidimensional sustainability metrics. Random Forest algorithm was selected for its ability to manage non-linear variable interactions and minimize overfitting.

In analyzing non-financial reports, sustainability policies, news coverage, and social media content, the study employs natural language processing (NLP) paradigms that facilitate semantic pattern extraction, risk detection (e.g. greenwashing), and latent ESG profiling. Explainable AI (XAI) methods-such as SHAP and LIME-are particularly relevant, as they ensure transparency in decision-making processes, which is critical for regulatory compliance and maintaining stakeholder trust (Sydoryuk & Leschiy, 2024).

Structurally, the integration of these analytical mechanisms involves embedding them into digital supply chain management platforms (SRM systems, e-procurement solutions), thereby enabling continuous ESG risk monitoring, automated supplier categorization, and prioritization. ESG indicators are formalized by converting qualitative descriptors into

numerical or categorical variables, which can then be processed through relevant mathematical models.

Within the applied implementation of this methodology, multi-criteria optimization algorithms are employed to balance cost, quality, and sustainability characteristics. Specifically, a Pareto optimization model was utilized to find optimal trade-offs between supplier scores, while an isolation forest algorithm was applied for anomaly detection, allowing us to flag sudden, high-risk drops in a supplier's ESG rating or performance. Additionally, anomaly detection scenarios can be developed to flag supplier behaviors indicative of reputational or regulatory threats.

Ethical Data Use and Governance. The rigor of AI models relies heavily on data quality, making ethical data sourcing and privacy non-negotiable. All data used in this study were sourced exclusively from publicly available corporate sustainability reports and verified news databases. To ensure transparency and mitigate the risk of algorithmic bias, all model outputs were rigorously cross-checked against manually coded ESG benchmarks throughout the training and validation phases. Furthermore, the models adhere to strict data privacy protocols: The analysis focuses only on aggregated, non-personally identifiable metrics (e.g., carbon intensity, labor violation rates) at the organizational and tier-level, ensuring supplier-specific proprietary information and individual personnel data remain anonymized and secured throughout the machine learning lifecycle.

ANALYTICAL SECTION

In the context of global supply chain transformation and increasing regulatory pressure on non-financial reporting, particularly in the area of sustainable development, Unilever stands out as a leading example of an ESG-oriented business with a high level of transparency. The selection of this case is driven by several factors. First, Unilever is a publicly traded company with a long-standing tradition of sustainability reporting aligned with GRI, CDP, and the UN SDGs, providing a reliable empirical foundation for modeling ESG behavior. Second, the company explicitly declares the integration of environmental, social, and governance principles into both internal operations and supplier relationships. Third, the availability and accessibility of open data make it possible to apply modern analytical tools, including AI / ML models, in a real-world context, thus aligning the research with practical applications in the corporate sector. The choice of the Unilever case is therefore both methodologically justified and representative of global trends in ESG integration within supply chain management (Unilever Sustainable Living Plan 2010 to 2020: Summary of 10 years' progress).

The object of analysis is Unilever's Sustainable Living Plan and its accompanying corporate sustainability reports. The purpose of the analysis is to demonstrate the potential for structured extraction of ESG indicators, their formalization, and subsequent analytical use within an automated supplier evaluation system.

At the initial stage, preprocessing of the available textual corpus was conducted using Natural Language Processing (NLP) techniques, such as tokenization, lemmatization, and named entity recognition, which enabled the identification of key reporting domains (e.g, greenhouse gas emissions, supply chain energy efficiency, labor rights compliance, governance transparency). Further analysis using topic modeling (LDA) and semantic encoding allowed for the identification of clusters of policies and practices directly linked to supplier assessment criteria: supply chain audits, requirements for environmentally safe raw material certification, and third-party verification of working conditions (Oxford Executive. Case study: Unilever's Sustainable Living Plan).

Particular attention was paid to the quantitative parameterization of declared ESG indicators. For instance, comparative analysis showed that Unilever reduced its CO₂ emissions per product unit by 18% over three years, while independent audit coverage of its supply chain increased from 62% to 87%. These numerical values were converted to an index scale (0 - 1) for subsequent use in a scoring model for supplier ranking. Additionally, a Random Forest classification was applied to identify the significance of specific ESG factors within the predictive model for supplier compliance (Mirza, 2024).

The integration of these analytical results into a prototype supplier evaluation model demonstrates the potential for developing a scalable and transparent decision-making system in the domain of sustainable procurement. Such a system enables simultaneous consideration of declared policies, actual indicator dynamics, and the degree of independent verification, critical for minimizing greenwashing risks and ensuring alignment with global sustainability standards.

To structure the ESG analysis results in Unilever's practice, publicly available non-financial reports, CSR declarations, and key sustainable sourcing parameters were consolidated. Unilever was intentionally selected as the representative case due to its long-standing, publicly transparent ESG reporting framework, its explicit alignment with global standards (such as GRI, CDP, and the UN SDGs), and the readily accessible longitudinal sustainability data, which together provide a robust environment for testing and demonstrating AI-based formalization techniques. Table 1 illustrates how specific quantitative and qualitative metrics allow for a structured evaluation of a supplier's performance across the three ESG dimensions- Environmental (E), Social (S), and Governance (G) – and how this data can be formalized for further algorithmic processing within AI systems:

Table 1: ESG Analysis of Unilever's Supplier Practices

ESG Category	Indicator / Metric	Data (2023)	Source / Note
Environmental (E)	Total supply chain CO ₂ emissions (Scope 3)	~63 million tons CO ₂ e	Unilever Climate Transition Action Plan
	Share of suppliers with Science-Based Targets	68%	Unilever Sustainability Progress Report
	Sustainable packaging policy	54% packaging is reusable or recyclable	Global Packaging Strategy
Social (S)	Supply chain inclusivity	64,000 MSMEs from developing countries are involved	Partner with Purpose Report
	Ethical labor certification programs	80% of sites audited via Sedex / SMETA	Unilever Human Rights Report
	Rights protection and feedback mechanisms	Confidential grievance mechanism at 100% Tier 1	Code of Business Principles
Governance (G)	Supplier ESG scoring	Internal rating + external agencies (EcoVadis)	Procurement Ethics Protocol

Procurement policy transparency	Full publication of Supplier Code of Conduct	Unilever Procurement Portal
Anti-corruption compliance	100% of suppliers are required to undergo compliance training	Ethics & Compliance Training

Source: Compiled by the author

The table illustrates the high level of ESG integration in Unilever’s supplier system, which encompasses both quantitative metrics (e.g Scope 3 emissions, percentage of sustainable packaging) and qualitative parameters (e.g ethics policies, certifications, transparency). From an algorithmic standpoint, this data structure is suitable for digital formalization as ESG scoring variables, forming the foundation for supplier ranking models using AI / ML techniques (Oxford Executive. Case study: Unilever’s.

Moreover, the identified metrics underscore the potential of explainable AI (XAI) technologies in procurement decision-making-for example, justifying supplier exclusion based on failure to meet minimum environmental or social compliance thresholds. Thus, the Unilever case study demonstrates not only empirical relevance but also the operational feasibility of ESG approaches within modern digital procurement platforms (Mirza, 2024).

Thorough analysis of Unilever’s supplier management practices reveals both a high degree of ESG integration and a growing need for automated tools to process large volumes of non-financial data. This observation logically leads to a discussion of AI-based methodological approaches for conducting deep and transparent ESG risk assessments in supply chains.

Given the increasing complexity of supplier evaluation in ESG-driven supply chain governance, artificial intelligence emerges as a critically important tool for enabling multidimensional risk analysis, something that traditional deductive methods cannot accomplish with sufficient depth or relevance. AI models not only scale supplier assessment but also enhance objectivity, transparency, and predictability in decisions about engaging or excluding counterparties.

The formalization of ESG indicators into structured variables (e.g supplier CO₂ emissions, employee engagement, compliance with anti-corruption protocols) enables the application of models such as decision trees, random forests, XGBoost, and neural network architectures to build ESG scoring systems tailored to specific sectors. Classification and regression models support both binary selection (compliant / non-compliant) and ranking suppliers by ESG risk level, critical for procurement prioritization.

Special attention should be paid to the use of Explainable AI (XAI) technologies, which provide transparency in algorithmic decisions and ensure compliance with regulatory requirements and internal compliance policies. Tools like SHAP (Shapley Additive exPlanations) or LIME (Local Interpretable Model-Agnostic Explanations) can identify the contribution of each ESG parameter to the overall supplier risk profile. This is essential both for internal auditing and for demonstrating due diligence as defined by OECD and ISO 20400.

Furthermore, applying NLP methods to unstructured sources-such as corporate reports, news flows, human rights reports, or social media content-supplements the structured model semantically. Tools like BERT or GPT-based classifiers can detect ESG deviations (e.g. scandals, strikes, environmental incidents) not reflected in official reporting but significantly affecting the cumulative ESG rating of a supplier.

In summary, the application of AI models to ESG-based supplier evaluation introduces a new level of analytical complexity, responsiveness, and compliance with ethical and regulatory standards. These technologies can transform supply chain management from reactive to proactive, enabling the early detection, classification, and mitigation of risks before supplier engagement occurs (Yu, Fan, & Yu, 2025).

Given this context, it becomes necessary to critically examine how the results generated by AI-based models differ from those of traditional evaluation systems, and how these differences affect the effectiveness of strategic procurement management. Within the framework of comparative analysis, it was found that the outcomes produced using AI models incorporating ESG factors demonstrate fundamental differences in both the content and structure of supplier rankings. Traditional approaches, which focus on parameters such as cost, delivery speed, and technical compliance, offer a narrow evaluative lens and fail to consider non-financial aspects that increasingly influence the stability of supply chains in the 21st century.

The comparison revealed that several suppliers who ranked highly under traditional methods, due to competitive pricing or technical capabilities, received low ESG scores under the AI-based evaluation. Reasons for such downgrades may include identified risks such as labor exploitation, non-compliance with environmental standards, absence of sustainability reporting, or negative media sentiment. In the long term, such suppliers pose significant operational risks, from breaches of contractual obligations to regulatory consequences or reputational damage to the purchasing company.

Moreover, AI-driven analytics can uncover latent risks that are not captured by rigid numerical metrics but can have a cumulative effect. For example, the absence of publicly available ESG policies, ambiguous stances on human rights, or negative sentiment analysis in the media discourse are all factors overlooked by traditional assessments, yet they may prove critical for the sustainability of a business partnership. Thus, the implementation of AI-based approaches not only adds complexity to the analytical model but also significantly expands the horizons of risk management. It enables decision-making based not solely on short-term economic benefits, but also on multidimensional assessments of the reputational, regulatory, and environmental context of potential suppliers (Segun-Ajao, 2025).

To align short-term business interests with long-term sustainability goals, a priority matrix is proposed that combines two key decision-making axes:

Horizontal axis – the cost attractiveness of the supplier (price, logistics costs, flexibility of conditions);

Vertical axis – ESG compliance (an integrated assessment based on environmental, social, and governance criteria, generated through AI analytics).

The matrix enables the classification of suppliers into four strategic quadrants Table 2.

Table 2: Supplier Classification Matrix

	High ESG Compliance	Low ESG Compliance
Low Cost	Ideal Suppliers – strategically prioritized partners recommended for long-term contracting.	Opportunistic Suppliers – cost-attractive but ESG-risky; require additional auditing or may be conditionally acceptable for short-term contracts.
High Cost	Sustainable Reserve – high-standard suppliers justified for critical projects or premium branding segments.	Undesirable Suppliers – excluded from the potential partner list due to excessive risks and low economic feasibility.

Source: Compiled by the author

The Supplier Classification Matrix (Figure 1) is a visualization tool that allows classification of counterparties according to two core criteria: procurement cost and ESG compliance. The x-axis represents cost characteristics (from low to high), while the y-axis represents the level of compliance with environmental, social, and governance principles.

1. Optimal Suppliers – those with low cost and high ESG rating, prioritized for engagement.
2. Sustainable Reserve – suppliers with high ESG ratings but higher costs; suitable as a strategic reserve or in ESG-sensitive contexts.
3. Opportunistic Suppliers – entities with attractive pricing but insufficient ESG compliance, posing potential reputational or regulatory risks.
4. Undesirable Suppliers – partners with both high costs and low ESG ratings; not aligned with sustainable sourcing principles and subject to exclusion from the supply chain.

This approach enables AI systems to generate strategically balanced decisions through multi-criteria optimization, ensuring both economic efficiency and long-term sustainability.

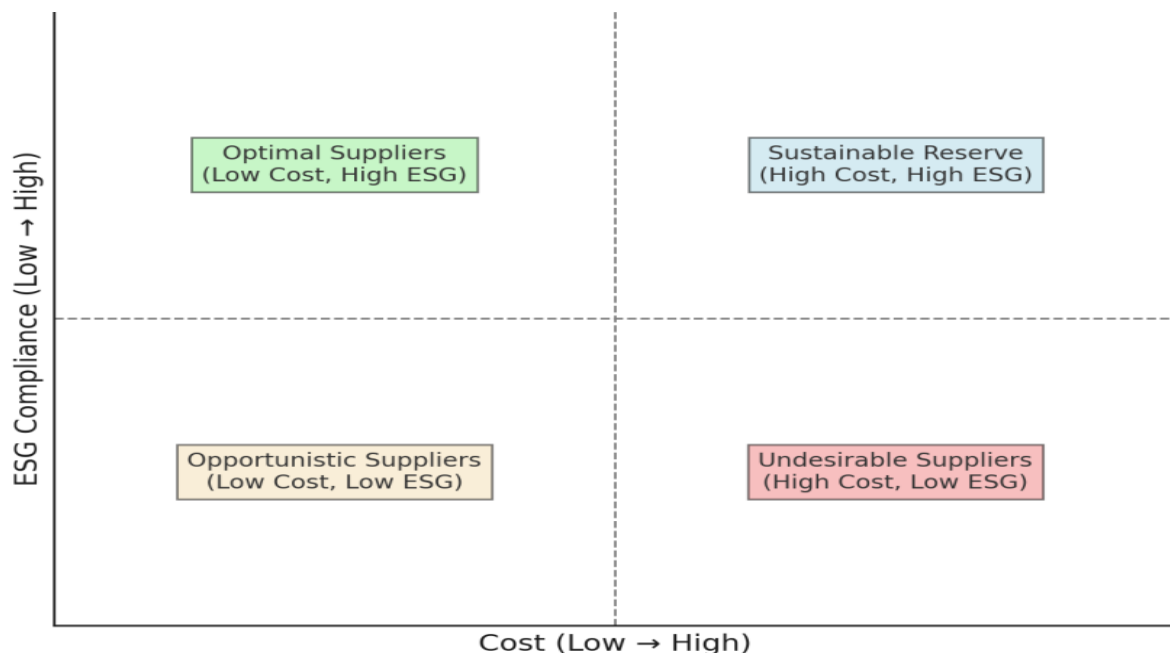


Figure 1: Supplier Classification Matrix.

Source: Compiled by the author

The supplier classification matrix can be implemented as an interactive module within an SRM (Supplier Relationship Management) system, integrating the following components:

1. A module for integration with open ESG registers and databases (such as EcoVadis, Refinitiv, CSRHub).
2. An AI-powered module for processing textual sources and social signals (ESG NLP).
3. A weighted scoring mechanism with the option for manual adjustments by compliance or sustainability experts.
4. An API for exporting ratings into internal ERP or eProcurement platforms.

The implementation of such a matrix allows companies to:

1. Shift from intuitive to algorithmic decision-making in procurement.
2. Develop a well-grounded and transparent supplier selection policy with consideration of ESG risks.
3. Balance procurement KPIs between cost-efficiency and corporate responsibility.
4. Reduce reputational and regulatory risks associated with unethical suppliers (Yu, Fan, & Yu, 2025).

Following the analysis of the supplier classification matrix, which revealed a range of options with varying degrees of compliance with both economic and ESG criteria, there is a clear need for a more sophisticated decision-making approach. The mere existence of alternatives with comparable cost competitiveness but significantly different environmental, social, or governance profiles illustrates the limitations of traditional one-dimensional selection models focused solely on cost optimization. Therefore, the logical next step involves transitioning to multi-criteria analysis that accounts for complex trade-off relationships between conflicting performance criteria.

Based on the results of a comparative analysis between traditional supplier assessment approaches and ESG-integrated analytics, a more complex decision model is required—one that incorporates multiple conflicting criteria. Classic trade-offs, such as cost-efficiency versus environmental responsibility or delivery speed versus social-ethical standards, necessitate the use of multi-objective optimization techniques. In this context, Pareto optimization and evolutionary algorithms (e.g. NSGA-II) are particularly valuable, as they enable the generation of a set of equally optimal alternatives. This lays the foundation for flexible, strategic decision-making in fast-evolving business environments.

To automate the processing of large-scale ESG data and identify nonlinear relationships among indicators, it is advisable to use deep learning methods. The application of multilayer neural networks (e.g. DNN or LSTM) enables the modeling of historical supplier behavior patterns, forecasting future ESG compliance, and adapting models to external changes. Combining such systems with explainable AI (XAI) ensures both performance and transparency of decisions, which are crucial for upholding accountability and building stakeholder trust (Rane, Desai, & Choudhary, 2024).

Given the capabilities of deep learning and evolutionary methods for solving complex multi-criteria supplier evaluation tasks, it becomes essential to understand the broader role of artificial intelligence as a driver of strategic change in sustainable procurement. Accordingly, it is appropriate to analyze the key benefits, limitations, and practical recommendations for integrating AI into procurement policies with consideration of ESG priorities.

In the context of supply chain digital transformation, artificial intelligence (AI) serves as a powerful enabler of strategic decision-making in sustainable procurement. Its ability to process

large volumes of ESG data, model complex interdependencies, and detect hidden patterns delivers an entirely new level of analytics, unattainable by traditional tools. AI enhances the objectivity of supplier evaluation, mitigates cognitive biases, and supports decisions based on transparent and formalized criteria. The scalability of such systems allows for the consistent application of ESG screening across global supply chains, while algorithmic adaptability ensures responsiveness to emerging risks, regulatory changes, and evolving standards of responsible business conduct.

Nevertheless, despite its significant potential, the use of AI in ESG contexts faces several challenges. Chief among them is the limited availability of high-quality, complete, and standardized ESG data, data-particularly from suppliers in low-regulation countries or smaller companies. Furthermore, the algorithmic complexity of deep neural networks raises the explainability problem-the inability of users or regulators to understand how AI-driven decisions are made, which undermines trust in such systems. This is a particular issue with suppliers in developing countries or with smaller companies, which may lack the resources for robust ESG reporting. Finally, ethical risks must be considered, including the replication of historical biases, ambiguous interpretations of social responsibility, or the misuse of ESG models for greenwashing. The danger of AI models perpetuating historical biases present in the training data, potentially leading to the unfair exclusion of certain types of suppliers. Addressing these issues requires not only technical solutions but also regulatory and institutional frameworks.

Based on the above, the following strategic recommendations are proposed:

1. Integrate the ESG-by-design principle into digital procurement platforms-embedding ESG criteria as a core element of the architecture of e-tendering systems, SRM platforms, and procurement CRMs. This will ensure a standardized approach to sustainable procurement at the infrastructure level.
2. Develop national ESG supplier evaluation methodologies aligned with international standards (GRI, SASB, CSRD). These methodologies should encompass both quantitative and qualitative metrics, be adapted to local contexts, and support the creation of open datasets for training AI systems.
3. Build feedback systems for AI learning based on real cases-creating mechanisms that allow AI systems to self-train using post-factum supplier evaluations, independent audits, and ESG-related incidents. This will enhance model responsiveness and relevance in real time (Xu, 2024).

Thus, the implementation of AI in sustainable procurement should be part of a broader transformation of institutional and technological environments. Only through such integration can organizations achieve a balance between innovation, transparency, accountability, and effectiveness in managing supplier risks in alignment with ESG principles.

CONCLUSIONS

Given the increasing complexity and multidimensionality of modern procurement processes, the integration of ESG criteria into supplier assessment procedures is not only an ethical imperative but also a strategic necessity for companies striving for long-term sustainability. In conclusion, the conducted study confirms the relevance of using AI-based models—including machine learning methods, deep neural networks, and multi-criteria optimization—as formalized, scalable, and adaptive tools for decision support in sustainable procurement. The Unilever case study provides a concrete example of practical ESG analytics implementation,

while simultaneously illustrating the limitations of traditional approaches that focus primarily on cost and technical parameters without accounting for environmental and social impacts. However, it must be noted that while the Unilever case study is representative of complex multinational firms, its findings may not be universally applicable across all industries or companies with significantly smaller supply chain footprints.

RECOMMENDATION

Based on these findings, we offer three core recommendations for organizations: (1) Implement the proposed AI-driven analytical matrix to enable multi-criteria optimization, balancing traditional metrics (cost, quality) with comprehensive ESG scores; (2) Adopt an ESG-by-Design approach by natively embedding sustainability governance and real-time data feeds directly into digital procurement platforms; and (3) Establish strong ethical governance around AI deployment to ensure data privacy, source credibility, and continuous algorithmic bias mitigation. To operationalize these insights, we recommend adopting ESG-by-design principles in procurement platforms and developing national ESG standards tailored to industry contexts. Particular attention should be paid to the development of national ESG supplier assessment standards tailored to industry-specific contexts, which would reduce interpretive variability and enhance data comparability. To increase the efficiency of AI systems, the establishment of feedback mechanisms based on real-life cases is advisable, as well as the advancement of explainable AI (XAI) to ensure decision transparency. Promising areas for future research include the application of generative AI for constructing ESG profiles of new suppliers and the formalization of responsible risk management models based on behavioral and non-financial indicators.

REFERENCES

- Abhayawansa, S., & Tyagi, S. (2021). Sustainable investing: The black box of environmental, social, and governance (ESG) ratings. *Journal of Wealth Management*, 24(4), 49–54. <https://doi.org/10.3905/jwm.2021.1.130>
- Fafaliou, I., Giaka, M., Konstantios, D., & Polemis, M. (2022). Firms' ESG reputational risk and market longevity: A firm-level analysis for the United States. *Journal of Business Research*, 149, 161–177. <https://doi.org/10.1016/j.jbusres.2022.05.010>
- Giudici, P., & Wu, L. (2025). Sustainable artificial intelligence in finance: Impact of ESG factors. *Frontiers in Artificial Intelligence*, 8, 1566197. <https://doi.org/10.3389/frai.2025.1566197>
- Mirza, Z. (2024, March 18). Unilever to scale back ESG pledges focused on plastic usage and diversity. *ESG Dive*. <https://www.esgdive.com/news/unilever-scale-back-esg-pledges-focused-plastic-usage-diversity/713882/>
- Oxford Executive. (n. d.). *Case study: Unilever's «Sustainable Living Plan»*. Retrieved June 29, 2025. <https://oxfordexecutive.co.uk/case-study-unilevers-sustainable-living-plan/>
- Rane, N. L., Desai, P., & Choudhary, S. (2024). Challenges of implementing artificial intelligence for smart and sustainable industry: Technological, economic, and regulatory barriers. *Artificial Intelligence for Industrial Society*, 5, 2–83. https://www.google.com/search?q=https://doi.org/10.70593/978-81-981271-1-2_5
- Segun-Ajao, E. (2025). *AI and sustainable procurement: A path to green supply chains*. Preprints. <https://doi.org/10.20944/preprints202501.1516.v1>

Sydoryuk, Y., & Leschiy, L. (2024). The future is now: Analysis of the AI market and its impact on business strategy and risks. *Problems of Modern Transformations. Series: Economics and Management*, (13). <https://doi.org/10.54929/2786-5738-2024-13-04-03>

Thomson Reuters Institute. (2024). *2024 Global Trade Report*. Thomson Reuters.

Unilever (2020). *Unilever Sustainable Living Plan 2010 to 2020: Summary of 10 years' progress*.

<https://www.unilever.com/files/92ui5egz/production/16cb778e4d31b81509dc5937001559f1f5c863ab.pdf>

Xu, J. (2024). *AI in ESG for financial institutions: An industrial survey*. SSRN.

<https://doi.org/10.2139/ssrn.4949354>

Yu, X., Fan, L., & Yu, Y. (2025). Artificial intelligence and corporate ESG performance: A mechanism analysis based on corporate efficiency and external environment. *Sustainability*, 17(9), 3819. <https://doi.org/10.3390/su17093819>

.....
Copyright: (c) 2025; Yuliia Zorina



The authors retain the copyright and grant this journal right of first publication with the work simultaneously licensed under a [Creative Commons Attribution \(CC-BY\) 4.0 License](https://creativecommons.org/licenses/by/4.0/). This license allows other people to freely share and adapt the work but must credit the authors and this journal as initial publisher.