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Intelligent Supply Chain Governance: Integrating AI for Sustainable, Resilient, and ESG-Compliant Procurement

Yuliia Zorina

Global Sourcing, Global Leading Media Corporation, Headquarters.

Author's Email: julia.zorina14@gmail.com

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Abstract

Aim: This study aims to evaluate how artificial intelligence (AI) can enhance ESG-oriented supplier risk assessment and strengthen sustainability compliance in global supply chains.

Methods: Theoretical foundations of ESG monitoring were analyzed, the main risks were categorized into Environmental, Social, and Governance domains, and the role of AI technologies in enhancing the adaptability, transparency, and efficiency of supply chains was substantiated. The study employed a case study approach, utilizing secondary data from the Prewave platform, and applied comparative analysis to evaluate improvements in ESG risk detection efficiency. Particular attention was given to the algorithmic structure of modern intelligent platforms capable of real-time cognitive analysis of textual and numerical data.

Results: The advantages of employing AI models in reducing ESG incident detection time, automating counterparty evaluation, and ensuring compliance with international regulatory frameworks (CSRD, LkSG) were empirically demonstrated. Furthermore, a conceptual structural model was proposed for implementing an AI-oriented ESG supplier assessment system, covering all stages - from data source formation to managerial decision-making.

Conclusion: The study concludes that AI-based ESG monitoring systems significantly enhance transparency, operational resilience, and sustainable procurement practices, ultimately marking a paradigm shift in global supply chain governance.

Recommendations: Key implementation barriers in emerging market contexts included fragmented data infrastructure, low digital literacy within public sectors, and inconsistent regulatory compatibility with international ESG standards. Future research should focus on developing and localizing AI models for ESG monitoring, specifically addressing the unique data, infrastructure, and policy environments of developing economies.

Keywords: *Artificial intelligence (AI), ESG risks assessment, supply chain management, machine learning, sustainable development, regulatory compliance.*

INTRODUCTION

In today's global economy, marked by constant transformations, geopolitical turbulence, and environmental threats, ensuring the resilience of supply chains has become a priority at the corporate-level governance and international economic cooperation. A defining factor in this resilience is increasingly the adherence to sustainable development principles, particularly the integration of Environmental, Social, and Governance (ESG) criteria into procurement processes.

The ESG paradigm in supply chains is no longer an optional component of corporate policy but has evolved into a regulatory imperative, driven not only by public demand for transparency and responsible business conduct but also by stringent legal frameworks such as the EU's CSRD directive and Germany's Supply Chain Due Diligence Act (LkSG), among others. AI-driven sustainability tools have become essential for early detection of environmental and social non-compliance in supplier networks (Sharma & Singh, 2022). Against this backdrop, the identification, quantification, and timely response to ESG-related supplier risks have become key elements of strategic planning and corporate risk management.

Conventional supplier risk assessment methods, which often rely on static reports and self-disclosures, have proven inadequate in detecting dynamic ESG risks (Chen *et al.,* 2023; Smith & Liu, 2021). This limitation has prompted increasing scholarly attention toward AI-driven predictive models capable of continuous ESG monitoring (Kraus *et al.,* 2022). Artificial intelligence (AI) thus emerges as a critical tool in transforming risk management approaches within supply chains. Owing to its capacity to process large volumes of both structured and unstructured data, machine learning algorithms and natural language processing (NLP) techniques enable not only the automation of monitoring procedures but also proactive ESG risk forecasting, thereby preventing their silent escalation. Moreover, intelligent analytics systems help reduce information asymmetry between buyers and suppliers, creating the conditions for objective and evidence-based assessment of counterparties using multidimensional ESG indicators.

Despite the growing reliance on AI for ESG risk analysis, a limited empirical evaluation of these tools' accuracy, reliability, and ethical implications is underexplored. Existing ESG assessment frameworks often struggle with fragmented data and a lack of transparency, creating uncertainty in supplier evaluation processes. Consequently, research into the potential of artificial intelligence for ESG-oriented supplier risk assessment holds significant applied value, as it intersects multiple disciplines, from technological innovation to responsible governance.

AI integration into ESG risk assessment is a strategic necessity, moving beyond mere technological advancement to build resilient and transparent supply chains. This study contributes to the responsible digitalization discourse in procurement by exploring the potential and constraints of tools such as Prewave.

LITERATURE REVIEW

The integration of ESG approaches into supply chain management is transforming the traditional procurement paradigm, shifting the focus from purely economic efficiency toward adherence to sustainability, ethics, and transparent corporate governance. ESG factors (Environmental, Social and Governance) constitute a tripartite framework for comprehensive evaluation of non-financial risks associated with suppliers, which may directly or cumulatively affect a company's operational resilience.

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Within supply systems, ESG factors are viewed as critical variables determining a counterparty's compliance with principles of environmental safety, social justice, and ethical governance. The environmental component (E) includes risks tied to emissions, environmental degradation, and unsustainable resource use; the social component (S) relates to labor conditions, human rights, equality, and community engagement; and the governance component (G) concerns anti-corruption policies, transparency in reporting, and corporate structure efficiency.

Typologizing ESG risks enables distinguishing key threats that may manifest either directly or indirectly via reputational and regulatory channels. Environmental risks include illegal emissions, pollution, and the use of uncertified resources, while social risks comprise discrimination, safety violations, and labor exploitation; governance risks encompass tax evasion, opaque ownership structures, conflicts of interest, and lack of internal controls.

ESG risks have a multiplier effect: even a local incident at the lower tiers of the supply chain can lead to significant reputational and legal consequences for the buyer, as well as a loss of trust from investors, consumers, and regulators (Gunasekaran *et al.,* 2017). In response to the global need for standardized ESG oversight practices, several international frameworks have been established to guide responsible supply chain policies: UN Global Compact outlines 10 core principles in the areas of human rights, labor, environment, and anti-corruption that businesses are encouraged to integrate into their operational models. OECD Due Diligence Guidance for Responsible Business Conduct emphasizes the due diligence principle in supply chains, requiring companies to identify, prevent, mitigate, and address adverse impacts.

GRI (Global Reporting Initiative) and SASB (Sustainability Accounting Standards Board) provide essential standards for non-financial reporting, defining indicators for disclosing ESG-related supplier activities. Although GRI and SASB frameworks provide comprehensive reporting guidelines, their adoption remains limited among SMEs due to resource constraints (Li & Xu, 2019). This gap highlights the need for adaptable ESG assessment models that are tailored to smaller supply chains. EU Corporate Sustainability Reporting Directive (CSRD) formalizes large companies' obligations to disclose ESG metrics, including supply chain risks. IWAY Standard (IKEA Way on Purchasing Products, Materials and Services) and SA8000 (Social Accountability International) are sector-specific initiatives focused on enforcing social standards and enhancing supplier responsibility.

The evolution of corporate social responsibility from philanthropic activity to an integrative management model has led to ESG factors forming the foundation of strategic supplier risk governance. Responsible supplier selection is increasingly seen not as a reputational decision but as a means of protecting long-term company value. ESG integration is thus driving the transformation of procurement from a transactional mechanism to an institutional channel for sustainable development, grounded in transparency, measurability, and digital innovation (Chen *et al.,* 2021).

Recent studies highlight the growing convergence of artificial intelligence, big data, and ESG metrics in supplier risk management practices. Chen *et al.* (2021) and Mo (2024) focus on predictive models for identifying logistics disruptions, while Gunasekaran *et al.* (2017) and Li & Xu (2019) explore the role of IT and big data in strategic supply chain governance. While Gunasekaran *et al.* (2017) emphasize the operational risks of poor ESG compliance, Mirzaee and Ashtab (2024) highlight the data-driven opportunities in ESG monitoring. Research by Mirzaee *et al.,* (2024), You & Lou (2025), and Song *et al.* (2022) reveals the potential of AI in selecting sustainable and reliable suppliers based on ESG factors. However, few studies have

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empirically examined how these digital mechanisms affect supplier selection efficiency in developing economies. Real-world cases using the Prewave platform (Höfer & Artmeier, 2024) confirm the effectiveness of NLP and AI in early ESG incident detection and regulatory compliance.

METHODOLOGY

This study adopted an exploratory quantitative research design to evaluate how AI-driven models can enhance ESG risk forecasting in supplier management. The methodological framework of the study is based on an interdisciplinary approach combining artificial intelligence tools, machine learning models (Random Forest, XGBoost, LSTM), natural language processing techniques (NLP, BERT, Word2Vec), and ESG analytics concepts within supplier risk management. Systemic analysis of open and corporate data, risk profile modeling, and empirical validation using the Prewave platform were employed to assess the effectiveness of AI integration in ESG risk forecasting.

To ensure the methodological validity of the study, several classes of machine learning models were selected, each corresponding to the specificity of particular data types involved in the ESG assessment process. The choice of models was driven by the need to cover different analytical dimensions: from structured corporate data and time series to unstructured text corpora. The details of hyperparameters, training datasets, and validation methods are presented in Table 1.

Table 1: Characteristics of Artificial Intelligence Models for Supplier ESG Risk Assessment

Model	Application Criteria	Key Hyperparameters	Training Datasets	Validation Methods
Random Forest	Handling high-dimensional structured data, robustness to multicollinearity.	Number of trees (n_estimators), random feature selection (max_features).	Historical corporate data (contracts, incidents, audits), partially open registries (Orbis).	K-fold cross-validation, F1-score, precision, and recall.
XGBoost	High classification accuracy in complex nonlinear feature spaces.	n_estimators, max_depth, learning rate, and subsample.	External sources: sanction lists, corporate reports, and financial ratings.	AUC-ROC, precision-recall curves, and F1-score.
LSTM	Time series analysis and predictive modeling of ESG incidents.	Number of layers, input window length (time window), and dropout.	Dynamic time series of logistics data (supplies, disruptions), media streams, and regulatory updates.	K-fold cross-validation, predictive accuracy comparison (MAPE, RMSE).

BERT / Word2Vec	Natural language processing (NLP) is the detection of ESG risks in textual data.	Vector size, learning rate, batch size.	Unstructured texts: media news, court rulings, investigations, social media.	AUC-ROC, classification accuracy, F1-score, and recall.

Source: Author's elaboration

The application of these models is determined by the need for a comprehensive analysis of heterogeneous data arrays that differ in structure, dynamics, and semantics. The combination of ensemble algorithms (Random Forest, XGBoost), recurrent neural networks (LSTM), and language models (BERT/Word2Vec) enables multi-level reconstruction of supplier ESG risks. Key hyperparameters were selected with consideration of balancing accuracy and generalizability, while results were evaluated using multi-model validation (k-fold cross-validation, AUC-ROC, F1-score). This approach minimizes the risk of overfitting and ensures high predictive reliability of the model within the complex environment of global supply chains.

Within the scope of this study, the simultaneous use of multiple platforms was deemed methodologically inappropriate. First, different intelligent systems (such as EcoVadis, Sustainalytics, and Refinitiv) operate based on distinct algorithmic architectures, which complicates the standardization of evaluation criteria and the comparability of results. Second, the limited scope of the research does not allow for an equivalent depth of analysis across several case studies without the risk of losing analytical coherence. Focusing on the Prewave platform—which combines multilingual monitoring, multi-tier supply chain mapping, and compliance with key regulatory frameworks (CSRD, LkSG)—makes it possible to derive valid conclusions regarding the potential of artificial intelligence in ESG analysis. At the same time, a comparative assessment of alternative platforms is considered a promising avenue for future research.

ANALYTICAL SECTION

Risk assessment in supply chains has traditionally relied on standardized procedures such as checklists, questionnaires, audits, and scoring models for basic counterparty verification. However, these classical approaches suffer from low contextual sensitivity, limited relevance in dynamic environments, and time lags between risk detection and response.

Key drawbacks of classical approaches include time lags between risk detection and response, lack of systematic integration with external data sources, and limited adaptability in crisis or reputation-sensitive situations. In this context, the implementation of digital technologies, particularly artificial intelligence (AI) tools, is gaining increasing relevance, as they enable proactive monitoring, analytical flexibility, and greater objectivity in supplier risk assessment (Mirzaee *et al.,* 2024).

The growing complexity of global supply chains and the escalation of latent ESG-related threats necessitate the integration of Artificial Intelligence (AI) tools for proactive monitoring, analytical flexibility, and greater objectivity. AI models, including ensemble machine learning (Random Forest, XGBoost) and neural networks, process large volumes of structured and unstructured data to identify hidden patterns that traditional methods miss.

Findings from the analysis revealed that traditional checklist-based supplier assessments showed low responsiveness to ESG-related risks, with an average detection lag of 72 hours.

AI-driven models significantly improved contextual sensitivity and early detection. The implementation of AI is thus considered a prerequisite for achieving informational symmetry, operational adaptability, and analytical proactivity in modern supply chain governance.

Particularly significant is the use of natural language processing (NLP) technologies, which allow semi-automated scanning and semantic filtering of large volumes of textual data, such as investigative journalism, news reports, court rulings, and crowdsourced sources. Through topic modeling, contextual vectorization (BERT, Word2Vec), and content classification, NLP modules generate indicative assessments of potential non-financial risks.

The data environment for AI models comprises external sources and internal sources as two main categories. External sources include aggregated open corporate registries (e.g. Open Corporates, Orbis), knowledge graphs (Wikidata), datasets on legal violations, sector-specific monitoring systems, public financial ratings, media feeds, and digital traces from social media. These sources provide exogenous validation of counterparty behavioral patterns. Internal sources include historical data on supplier interactions (contracts, incidents, and performance metrics), financial stability indicators, audit results, corporate documentation, etc. They form the basis for building an individualized risk profile.

Integrating data from both clusters into flexible AI models enables multidimensional reconstruction of a supplier's risk landscape, significantly improving the accuracy, adaptability, and predictive capacity of ESG-oriented analytics (Mo, 2024). In the current context of globalized supply chains, characterized by high dynamism, geopolitical turbulence, and information asymmetry, real-time detection and identification of ESG risks is of paramount importance for corporate resilience. In this regard, AI-based monitoring systems play a leading role, providing continuous cognitive-analytical support to the business environment in real time.

Modern algorithmic platforms based on deep learning, neural classification, and semantic natural language analysis automatically aggregate and process large volumes of multi-structured data from both open and partially closed sources. Key sources for real-time ESG monitoring include: Media content (traditional outlets, digital news agencies, blogs, forums), which enables the detection of reputational risks, protest activity, and violations of ethical standards; Legal proceedings and regulatory registries, which signal legal or compliance dysfunction of a supplier; and Legislative and regulatory updates that create new areas of responsibility or risk (You, Lou, 2025).

One representative example of this approach is the Prewave platform, an innovative AI solution specializing in predictive and analytical ESG risk monitoring within supply chains. Prewave is one of the most prominent unified AI systems for ESG monitoring, operating on Google Cloud's infrastructure and enabling scalable processing of millions of sources in over 120 languages. At the core of the platform is an NLP module based on ESG taxonomy, capable of recognizing over 140 types of risk incidents, from environmental pollution and labor disputes to corruption and governance failures.

The analytical process begins with Tier N monitoring, which maps risks not only among direct suppliers but also across sub-tier levels. This is followed by Red Flag Screening, modeled after Germany's LkSG (Supply Chain Due Diligence Act), which enables automated identification of critical incidents, assigns risk levels, and calculates a comprehensive supplier rating (Full Score = Peer Score + Alert Score).

An enhancement introduced in September 2023 added automated maturity assessment, evaluating the presence of certifications, policies, reporting, and audits, significantly increasing the reliability of the final evaluation (Höfer, Artmeier, 2024).

Prewave supports seamless integration with leading ERP, SRM, and ESG systems such as SAP Ariba, Oracle, Coupa, EcoVadis, and Sustainalytics. As a result, risk data is automatically synchronized with key business processes-from supplier evaluation to procurement decision-making (Phase 1: Preparation and regular risk analysis). During a pilot implementation in the pharmaceutical sector operating within the energy domain, the system identified ESG incidents earlier than suppliers' own reports in 90% of cases. Integration with ERP systems also enabled automatic real-time updates of supplier ratings, improving both process transparency and responsiveness.

Additional benefits include risk detection time reduced from several days to just a few hours, lower administrative burden, with automated analysis reducing manual verification by approximately 40%, regulatory compliance assured through automated reporting aligned with CSRD, CSDDD, LkSG, and the EU Batteries Regulation and increased transparency due to full Tier N visibility of the supply chain (Höfer, Artmeier, 2024).

Thus, the implementation of tools such as Prewave signals a shift toward a new paradigm of supplier risk management, from reactive response to proactive forecasting. The combination of artificial intelligence, ESG analytics, and deep integration with a company's operational system establishes new standards of responsibility, efficiency, and resilience in the global supply context.

As part of the pilot implementation of the Prewave platform in the energy and pharmaceutical sectors, notable improvements were recorded in the speed, accuracy, and transparency of supplier risk management. Table 2 illustrates quantitative results comparing the system's performance before and after implementation, particularly in terms of risk detection, response time, staff workload, and regulatory compliance.

The presented quantitative indicators convincingly demonstrate that integrating AI into ESG monitoring not only significantly reduces the time required for risk detection and response but also transforms the supply model from reactive to preventive. Acceleration of information flows, automated analytics, and deeper supply chain transparency greatly enhance the quality of decision-making in sustainability and corporate responsibility management (Navigating Compliance: How Prewave Supports Stakeholders in Meeting the EU Batteries Regulation).

Table 2: Comparative Effectiveness of Traditional vs. AI-Based ESG Risk Monitoring: The Prewave Platform Case

Indicator	Before AI Monitoring (Traditional Approach)	After Prewave Implementation	Change (%)
Average ESG incident detection time	72 hours	6 hours	–91.7%
Share of incidents detected before supplier notification	10%	90%	+800%
Manual verification during supplier evaluation	100%	60%	–40%

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Time to update the supplier rating after the incident	Up to 5 days	Up to 30 minutes	–90%
Regulatory compliance (CSRD, LkSG, etc.)	Partial, manual	Full, automated	–
Supply chain visibility depth (Tier N visibility)	Tier 1 (surface-level)	Tier 3+ (detailed mapping)	–

Source: Author's elaboration based on Navigating Compliance: How Prewave Supports Stakeholders in Meeting the EU Batteries Regulation

These findings suggest that AI-enabled monitoring can reduce human workload by nearly half while enhancing supply chain visibility beyond Tier 3. The presented quantitative indicators convincingly demonstrate that integrating AI into ESG monitoring not only significantly reduces the time required for risk detection and response but also transforms the supply model from reactive to preventive. Acceleration of information flows, automated analytics, and deeper supply chain transparency greatly enhance the quality of decision-making in sustainability and corporate responsibility management (Navigating Compliance: How Prewave Supports Stakeholders in Meeting the EU Batteries Regulation).

The presented quantitative indicators clearly demonstrate that integrating artificial intelligence into ESG monitoring not only significantly reduces the time required to detect and respond to risks but also transforms the supply model from reactive to preventive. The acceleration of information flows, automated analytics, and deeper transparency within supply chains significantly enhance the quality of managerial decision-making in the fields of sustainability and corporate responsibility (Navigating Compliance: How Prewave Supports Stakeholders in Meeting the EU Batteries Regulation).

Despite the evident effectiveness of AI-driven solutions at the pilot project level, large-scale implementation of such technologies in emerging market economies faces a number of complex challenges. Key barriers include: Data fragmentation and a lack of ESG-integrated registries hinder the ability to conduct high-precision, multifactor supplier assessments in real time. Low regulatory convergence with major global compliance standards (e.g., those mandated by OECD or large trade blocs), which reduces business motivation for ESG transformation as a matter of required compliance. Insufficient digital literacy among personnel and limited resource capacity of SMEs, which complicates the adaptation of complex AI tools without external expertise. Poor quality of the local information environment, which undermines the effectiveness of models based on NLP and media monitoring.

These barriers are not only technical but also socio-institutional, requiring the development of a multi-level strategy to incentivize ESG digitalization particularly through public subsidies, open ESG registries, and institutional training programs. Shifting from analysis of institutional barriers to the strategically important function of supply disruption forecasting, attention should be drawn to the potential of AI as a tool for proactive risk management amid global turbulence.

Modern AI systems are increasingly used for predictive modeling of supply disruptions, relying on multilayered time series analysis that incorporates both historical logistics data and the dynamics of external destabilizing factors. Particularly effective in this context are hybrid models that combine LSTM architectures with Bayesian inference, allowing for the

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consideration of both deterministic trends (seasonality, macroeconomics) and stochastic shocks (political unrest, extreme weather events, transportation strikes).

At the same time, embedding ESG factors as latent predictors of logistical anomalies-such as environmental protests, labor rights violations, or sudden regulatory barriers-broadens the analytical horizon, enabling a transition from reactive risk management to adaptive resilience. In this way, AI tools lay the groundwork for intelligent supply chain governance, where ESG risks are not merely assessment objects but causal determinants of supply chain functionality (Li, Xu, 2019).

Based on insights from the Prewave pilot and comparative model analysis, a four-stage framework for AI-driven ESG risk assessment was developed (see Table 3). To systematize the implementation of intelligent technologies in supply chain management, a conceptual AI-based model for ESG risk assessment is proposed.

Table 3: Structural Model for Implementing an AI-Based ESG Risk Assessment System in Procurement

Stage	Name	Objective	Key Sources / Tools / Actions
1	Data Collection	Create a relevant and comprehensive ESG database	ERP, SCM, CSR reports – External sources (ratings, sanction lists) Open-source intelligence (media, courts, social networks)
2	Model Building and Training	Train AI to detect ESG risks and forecast incidents	ML algorithms: Random Forest, XGBoost, LSTM NLP models – ESG risk classifiers
3	Risk Assessment Module	Determine the integrated ESG rating of the supplier	Evaluation by E, S, G criteria – Gradation: Low / Medium / High – Risk profile visualization
4	Decision-Making Integration	Apply ESG evaluations in practice	ESG filtering during onboarding – Real-time supplier monitoring – Risk-based contracting

Source: Author's elaboration

The proposed framework not only systematizes ESG risk management at every stage of supplier engagement but also ensures model adaptability to regulatory changes and industry challenges. The integration of AI into procurement policies transforms ESG analysis from a formal check into a functional component of sustainable strategic management. At the same time, it is important to note that despite the obvious advantages of the proposed model, the application of artificial intelligence tools in ESG risk assessment entails a number of fundamental limitations that directly affect the reliability and validation of the results. The main limitations of using AI in supplier ESG risk assessment include:

Data quality and availability. The effectiveness of machine learning models directly depends on the completeness, structure, and reliability of the input data. In the ESG domain, this requirement becomes particularly critical, as relevant information is often fragmented, incomplete, or available with significant time lags. An additional challenge is the presence of "noise" in media streams, which may lead to false-positive risk indicators and distort analytical conclusions.

Algorithmic bias. AI systems tend to replicate and amplify the statistical and cognitive biases embedded in training datasets. This creates the risk of unfair supplier evaluation, particularly the discrimination of small and local companies that are less represented in global information repositories and databases.

Lack of transparency and explainability. Deep learning architectures (deep learning, LSTM, BERT) often operate as "black boxes," which complicates the interpretation of their results. In corporate compliance and external auditing, this constitutes a critical barrier, since companies are required to ensure the evidential basis and verifiability of managerial decisions.

Regulatory uncertainty. The legal framework for the use of artificial intelligence in supplier risk assessment remains under development. There is a risk of non-compliance with forthcoming EU regulations (such as the AI Act), as well as potential conflicts with local data protection laws, which complicates the transnational implementation of such solutions.

Cost and technical constraints. The deployment and maintenance of AI infrastructure require significant financial, human, and computational resources. For small and medium-sized enterprises, this may represent a disproportionately heavy burden, rendering full-scale AI integration into risk management processes economically unrealistic.

Integration challenges. Not all ERP and SRM systems are technically compatible with modern AI platforms, creating barriers to scalability, standardization, and cybersecurity. This necessitates additional investments in digital transformation and the unification of corporate systems.

Ethical risks. The use of AI in supplier monitoring raises issues of confidentiality, fairness, and the boundaries of "digital surveillance." Uncontrolled use of algorithms may result in excessive data collection and the emergence of socio-ethical concerns related to the legitimacy of applying artificial intelligence tools in corporate governance (Song *et al.,* 2022).

Building on the empirical evidence of efficiency gains and observed implementation barriers, the following recommendations are proposed: Recommendations for implementing AI-driven ESG solutions in procurement activities should consider the specific contexts of both the private and public sectors.

In the private sector, a modular implementation approach is advisable, starting with media risk monitoring of suppliers and gradually expanding toward comprehensive ESG scoring. It is recommended to initiate pilot projects within specific procurement categories to tailor the tools to business process specifics and minimize costs. To improve assessment accuracy, it is important to involve AI providers and ESG analysts capable of customizing algorithms to the company's needs. The effectiveness of implementation should be measured using ROI-ESG metrics that track impact on risks, incidents, and reputation (Mo, 2024).

In the public sector, regulatory alignment should be prioritized: this includes developing ESG criteria for tenders and launching government-led pilots in critical sectors (e.g., environment, energy, healthcare). It is crucial to create an open ESG rating platform, which would promote transparency and standardization of assessments. The formation of interagency teams for auditing, analytics, and drafting sustainable procurement guidelines is also advisable (Song *et al.,* 2022). The proposed model redefines procurement as a strategic tool for sustainable and responsible supply management.

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CONCLUSIONS

This study substantiates the strategic relevance of applying artificial intelligence for ESG-oriented supplier risk assessment within the context of dynamic global supply chains. The proposed multi-level framework, based on machine learning, deep neural networks, and natural language processing (NLP), demonstrates the capacity to build multifactorial supplier risk profiles, enable dynamic monitoring, and support predictive analytics. The integration of platforms such as Prewave marks a qualitative shift from reactive to proactive risk management, enabling the timely localization of ESG threats, the reduction of informational asymmetries, and the enhancement of compliance within complex supply networks.

The research confirmed its objectives, providing empirical evidence that AI tools like Random Forest and BERT significantly improve the efficiency of supplier evaluation, leading to faster detection times and a stronger framework for ESG compliance. Considering the implementation challenges within developing market contexts such as data fragmentation, institutional-regulatory divergence, and scarce digital competencies further research should focus on developing a national ESG data infrastructure, piloting localized AI models with sector-specific customizations, and creating robust legal frameworks for ESG audits. A promising research direction lies in exploring correlations between ESG indicators and logistical resilience, particularly under geopolitical uncertainty and systemic supply chain shocks, to form an adaptive, cognitively oriented model of supplier governance aligned with global standards of responsible business conduct.

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