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AI-ENABLED ESG RISK MONITORING FOR RESILIENT REGIONAL INDUSTRIAL SUPPLY CHAINS

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Abstract: This article develops a methodological framework for applying artificial intelligence to Environmental, Social and Governance (ESG) risk monitoring in regional industrial supply chains. The study argues that ESG management becomes more effective when environmental, social and governance data are transformed into early-warning signals rather than used only for retrospective reporting. Using the IMRAD structure, the research combines comparative analysis, process mapping, indicator grouping, a five-point risk assessment and conceptual modelling. A Regional ESG Resilience Index is proposed to evaluate energy and climate exposure, supplier responsibility, workforce safety, data reliability and governance transparency. The results show that AI-supported monitoring can identify abnormal resource consumption, emerging supplier risks, unsafe operational patterns and reporting gaps before they develop into major disruptions. However, the effectiveness of the system depends on data quality, human oversight, cybersecurity and clearly assigned managerial responsibility. The proposed framework includes three tables and three analytical diagrams and may be adapted by industrial enterprises, regional authorities and investors seeking to improve sustainability, resilience and investment attractiveness. [1–8]

Keywords: ESG, artificial intelligence, regional industry, supply chain resilience, risk monitoring, sustainability reporting, responsible business conduct, industrial competitiveness.

1. Introduction

Regional industrial supply chains are increasingly exposed to energy-price volatility, climate-related disruption, water stress, supplier non-compliance, labor-safety incidents and governance failures. These risks affect not only individual enterprises but also employment, tax revenues, export capacity and the stability of local value chains. Traditional control systems often identify problems after losses have already occurred. Therefore, sustainable industrial management requires an early-warning approach that connects operational data with ESG-based decision-making.

ESG provides a structured perspective for evaluating environmental impacts, social responsibility and governance quality. The Global Reporting Initiative focuses on an organization's most significant impacts on the economy, environment and people, while IFRS S1 and IFRS S2 require decision-useful information on sustainability-related and

climate-related risks and opportunities. These approaches show that sustainability information should support management and resource-allocation decisions, not merely public communication. [1–6]

Artificial intelligence can strengthen this process by analyzing large volumes of data from meters, enterprise systems, supplier records, audits and worker-safety reports. Machine-learning models can detect anomalies, classify suppliers, forecast resource demand and prioritize risks. Nevertheless, AI should not be treated as an autonomous substitute for governance. Its outputs must be transparent, verifiable and connected to accountable human decisions.

The purpose of this study is to develop a scientific and practical framework for AI-enabled ESG risk monitoring in regional industrial supply chains. The objectives are to: identify priority ESG risks; develop a measurable indicator system; propose an integrated resilience index; evaluate expected effects; and formulate a phased implementation roadmap.

2. Materials and Methods

The research applies systematic literature review, comparative analysis, process mapping, indicator grouping, conceptual modelling and expert-oriented scoring. The analytical unit is a regional industrial supply chain consisting of focal enterprises, suppliers, logistics providers, contractors and public institutions. The assessment follows the logic of risk identification, data collection, algorithmic analysis, managerial response and performance verification.

The methodological foundation combines impact reporting, sustainability-related financial disclosure and responsible-business-conduct due diligence. OECD guidance emphasizes risk-based due diligence across operations, supply chains and business relationships. Corporate-governance principles also require timely and accurate disclosure of material sustainability and governance matters. These principles were used to define the monitoring cycle and accountability requirements. [6–8]

Table 1. Methodological framework for AI-enabled ESG risk monitoring[7]

Stage	Assessment focus	Main tools	Expected result
1	Supply-chain process mapping	Document review, stakeholder interviews	Critical processes and dependencies identified
2	ESG risk identification	Materiality analysis, risk register	Priority environmental, social and governance risks
3	Data architecture	ERP, IoT, audit and supplier data inventory	Reliable variables and data gaps identified
4	AI-supported analysis	Anomaly detection,	Early-warning signals

[7] Global Reporting Initiative. (2021). GRI 1: Foundation 2021.

2. Global Reporting Initiative. (2021). GRI 2: General Disclosures 2021.

3. Global Reporting Initiative. (2021). GRI 3: Material Topics 2021.

		classification, forecasting	and risk priorities
5	Management response	Corrective actions, internal control and audit	Reduced disruption and improved accountability

The proposed Regional ESG Resilience Index (RERI) is calculated as: RERI = 0.25EC + 0.20SR + 0.20WS + 0.15DQ + 0.20GT, where EC is environmental and climate resilience, SR is supplier responsibility, WS is workforce safety and capability, DQ is data quality, and GT is governance transparency. Each block is scored from 0 to 5. A higher score indicates stronger resilience and more mature ESG integration. The weights are an author-developed methodological proposal and can be adapted to sectoral conditions. (author-developed methodology)

Figure 1. Integrated architecture of AI-enabled ESG risk monitoring

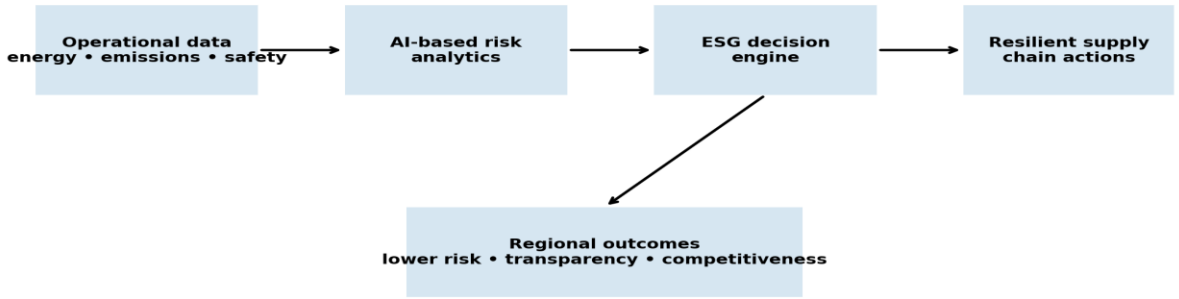

Figure 1 presents the proposed architecture. Operational information is collected from production, logistics, safety and supplier systems. AI-based analytics transform the data into risk signals. An ESG decision engine then connects each signal with a responsible unit, threshold and corrective action. The final outcome is a more resilient regional supply chain with lower losses, stronger transparency and improved competitiveness.

3. Results

The study identifies five priority risk groups for regional industrial supply chains. Environmental and climate risks include energy inefficiency, water stress, emissions and physical disruption. Supplier risks include weak compliance, unstable delivery, lack of certification and hidden environmental or labor violations. Social risks include occupational accidents, insufficient training and workforce instability. Data risks include incomplete, delayed or inconsistent information. Governance risks include unclear responsibility, weak internal control and low disclosure quality.

The results indicate that AI creates the greatest value in three situations. First, it identifies unusual patterns that are difficult to detect manually. Second, it integrates data from several departments and suppliers. Third, it prioritizes risks according to expected impact and urgency. For example, a simultaneous rise in energy intensity, equipment temperature and maintenance delays may signal an operational risk before production stops.

Table 2. Core indicators for regional ESG resilience assessment

ESG block	Indicator	Measurement unit	AI application	Management meaning
Environmental	Energy intensity	kWh per unit	Anomaly detection and forecasting	Identifies inefficient processes and cost exposure
Environmental	Water-risk exposure	0–5 score	Scenario and location analysis	Shows vulnerability to regional water stress
Social	Safety incident frequency	Rate per hours worked	Pattern recognition	Supports preventive safety actions
Social	Training adequacy	Hours/competency score	Skills-gap classification	Measures readiness for digital-green transition
Governance	Supplier ESG compliance	Percent/0–5 score	Supplier classification	Improves responsible procurement
Governance	Data completeness	Percent	Automated quality checks	Strengthens reliability of decisions
Governance	Disclosure maturity	0–5 score	Text and evidence consistency checks	Improves transparency and auditability

Table 2 shows that AI-supported ESG management requires both physical indicators and institutional indicators. A company may reduce energy use but still remain vulnerable if supplier information is incomplete or governance responsibilities are unclear. Therefore, resilience should be measured as a balanced capacity to prevent, absorb and respond to environmental, social and governance shocks.[8]

[8] IFRS Foundation. (2023). IFRS S1: General Requirements for Disclosure of Sustainability-related Financial Information.

5. IFRS Foundation. (2023). IFRS S2: Climate-related Disclosures.

6. OECD. (2023). OECD Guidelines for Multinational Enterprises on Responsible Business Conduct.

Figure 2. Illustrative ESG risk reduction profile

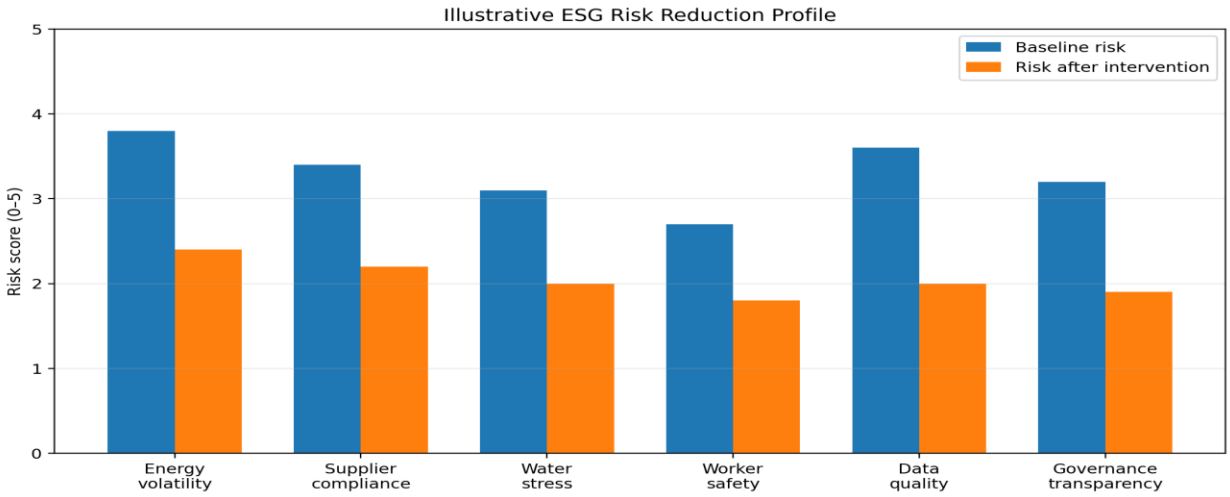

Figure 2 provides an illustrative comparison between baseline risks and the risk level after targeted intervention. The largest reductions are achieved in data quality, supplier compliance and governance transparency because AI improves visibility and prioritization. However, environmental and safety risks cannot be solved by analytics alone; they also require technological modernization, training and investment.

Table 3. Maturity levels of AI-enabled ESG risk management

Maturity level	Score interval	Main characteristics	Recommended action
Initial	0.0–1.0	Fragmented data; ESG actions are mainly reactive	Create a risk register and assign responsibilities
Basic	1.1–2.0	Selected indicators are collected; limited supplier coverage	Standardize data and introduce simple alerts
Integrated	2.1–3.0	Operational and ESG data are connected in key processes	Use predictive analytics and internal audit
Advanced	3.1–4.0	AI supports cross-functional and supplier decisions	Expand scenario analysis and assurance
Resilient	4.1–5.0	Continuous monitoring, transparent governance and learning	Scale regional collaboration and innovation

The maturity model demonstrates that AI-enabled ESG management should develop gradually. At the initial level, the priority is not sophisticated algorithms but reliable definitions, ownership and data collection. At the integrated and advanced levels, enterprises can use forecasting, supplier segmentation and scenario analysis. At the resilient level, monitoring becomes continuous and is linked with strategy, investment, audit and stakeholder communication.

Figure 3. Roadmap for implementing AI-enabled ESG monitoring

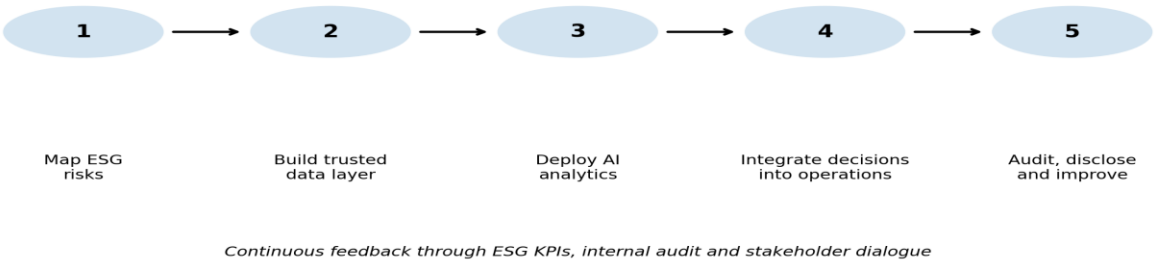

Figure 3 presents the implementation sequence. The first stage maps material ESG risks. The second establishes a trusted data layer. The third introduces AI analytics through pilot projects. The fourth integrates alerts into procurement, maintenance, logistics and human-resource decisions. The final stage verifies results through internal audit, disclosure and continuous improvement.[9]

4. Discussion

The proposed framework confirms that AI can improve ESG performance only when it is embedded in business processes. An algorithm that detects risk without a defined response process creates information but not resilience. Therefore, each model output should be connected with thresholds, responsible managers, evidence requirements and escalation procedures.

The framework also supports the integration of impact materiality and financial materiality. GRI-based reporting helps enterprises understand significant impacts on people and the environment, whereas IFRS sustainability standards focus on information relevant to providers of capital. Combining these perspectives allows regional enterprises to manage broader societal impacts while also improving investor confidence. [1–5]

Important limitations remain. AI models may reproduce bias contained in historical data, generate false alerts or become difficult to explain. Connected systems may also increase cybersecurity exposure. Smaller enterprises may lack specialist staff and reliable digital infrastructure. For these reasons, human oversight, periodic validation, cybersecurity controls and proportional implementation are essential.

The research is conceptual and should be tested using enterprise-level and regional data. Future studies may estimate sector-specific weights, compare different industrial regions, and measure the relationship between RERI scores, productivity, accident rates, emissions, supply disruptions and investment performance.

5. Conclusion

9 OECD. (2018). OECD Due Diligence Guidance for Responsible Business Conduct.

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The study concludes that AI-enabled ESG risk monitoring can become an effective management instrument for resilient regional industrial supply chains. It enables enterprises to move from retrospective reporting toward prevention, forecasting and coordinated response. The proposed RERI index, indicator system, maturity model and implementation roadmap provide a structured basis for practical assessment.

The main recommendations are to establish a reliable ESG data architecture, integrate supplier information, define risk thresholds, begin with focused AI pilots, train employees, preserve human accountability and verify outcomes through audit. Regional authorities can support this transformation through shared methodological guidance, digital infrastructure, green-finance mechanisms and cooperation platforms.

Overall, AI should be used not as a replacement for responsible governance but as a tool that improves visibility, speed and evidence-based decision-making. When combined with international ESG standards and risk-based due diligence, it can strengthen environmental responsibility, worker protection, corporate transparency and long-term regional competitiveness. [1–11]

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