Concept Paper

Not peer-reviewed version

Generative-AI Decision-Support and Optimisation Framework for Sustainable Logistics Resilience in Industrial Supply Chains – Example of Special-Purpose Mining Shaft Hoist Ropes

Marek R. Helinski *

Posted Date: 8 January 2026

doi: 10.20944/preprints202601.0628.v1

Keywords: generative AI; decision-support systems; sustainable logistics; supply-chain resilience; carbon border adjustment mechanism (CBAM); digital product passport (DPP); AI governance

Concept Paper

Generative-AI Decision-Support and Optimisation Framework for Sustainable Logistics Resilience in Industrial Supply Chains – Example of Special-Purpose Mining Shaft Hoist Ropes

Marek R. Heliński

Independent International Business Development Expert, Warsaw, Poland; helinski@wp.pl

Abstract

This paper develops a generative AI decision-support and optimisation framework for advancing sustainability and resilience in industrial logistics. The framework combines data aggregation, generative scenario creation, simulation-based evaluation, and multi-objective optimisation to support evidence-based management under tightening European Union sustainability regulations. Building upon the decision-aid lineage of the *International Journal of Production Research*, it integrates policy variables such as the Carbon Border Adjustment Mechanism (CBAM), the EU Emissions Trading System for maritime transport, FuelEU Maritime, the Digital Product Passport (DPP), and the Corporate Sustainability Reporting Directive (CSRD) directly into logistics-planning equations. Recent studies on digital twins and adaptive optimisation (Longo et al., 2023; Flores-García et al., 2025) highlight the need for AI systems that translate these policies into dynamic cost and carbon trade-offs. The proposed model responds to this need by coupling generative scenario synthesis with traceable optimisation and governance controls consistent with the EU AI Act (European Commission, 2025). An illustrative case from the mining-rope industry demonstrates how global sourcing and transport routes in European, South African, and Chinese configurations can be simulated within the generative environment to evaluate comparative cost, emission, and compliance profiles. Both SME-light and enterprise implementations achieved reduced analysis time and improved transparency of carbon-related decisions. The study contributes a replicable methodology that transforms generative AI from a creative text tool into a quantifiable governance instrument, linking strategic foresight with operational resilience in sustainable logistics networks.

Keywords: generative AI; decision-support systems; sustainable logistics; supply-chain resilience; carbon border adjustment mechanism (CBAM); digital product passport (DPP); AI governance

1. Introduction and Motivation

Global supply chains are experiencing increasing turbulence caused by geopolitical disruptions, energy volatility, and environmental regulation. These dynamics have intensified the need for decision-aid models capable of combining operational efficiency with sustainability and resilience. Traditional optimisation and simulation methods have provided valuable tools for planning production and logistics networks (Dolgui et al., 2018; Tiwari and Gupta, 2015). However, they often assume static data and limited policy feedback, which reduces their usefulness under evolving climate-policy frameworks.

The transition toward sustainable and digitally integrated supply chains in Europe has been accelerated by regulatory initiatives such as the Green Deal, the Carbon Border Adjustment Mechanism (CBAM), the EU Emissions Trading System for maritime transport, and the Corporate Sustainability Reporting Directive (CSRD). These measures redefine competitiveness by incorporating carbon cost, disclosure, and traceability as new decision variables. Firms now face pressure to evaluate not only the economic but also the environmental and regulatory implications of their logistics choices.

Parallel to these policy changes, rapid advances in artificial intelligence have expanded the toolkit available for logistics decision support. Machine-learning applications already contribute to demand forecasting, routing, and inventory optimisation (Wamba et al., 2021; Flores-García et al., 2024). Yet, most implementations remain predictive rather than generative. They help interpret existing data but rarely create alternative strategies or simulate future conditions. Generative AI introduces a new paradigm that can synthesise scenarios, explore trade-offs, and propose policy-compliant solutions by combining data reasoning with language-based modelling (Baryannis et al., 2019; Longo et al., 2023).

In this context, the present research addresses a dual gap. First, it explores how generative-AI architectures can extend classical IJPR decision-aid models toward adaptive scenario generation and multi-objective optimisation. Second, it integrates European sustainability regulations directly into the decision logic so that carbon-pricing mechanisms, emission limits, and traceability requirements become dynamic planning parameters rather than external constraints. The goal is to demonstrate that AI-enhanced models can bridge the long-standing divide between algorithmic optimisation and managerial usability.

The paper therefore proposes and tests a Generative-AI Decision-Support and Optimisation Framework for sustainable logistics. Using the mining-rope industry as an illustrative case, the study demonstrates how generative modelling can identify resilient and low-carbon logistics configurations under diverse regulatory scenarios. The approach supports both small and large enterprises, emphasising replicability, data transparency, and managerial interpretability.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on decision-aid models, resilience, sustainability, and AI applications in logistics. Section 3 introduces the proposed conceptual framework. Section 4 applies it to the mining- rope logistics case. Section 5 presents comparative evaluation, Section 6 outlines managerial implications, Section 7 discusses research perspectives and limitations, and Section 8 concludes.

2. Literature and State of the Art

2.1. Decision-Aid Models in Production and Logistics

Decision-aid modelling is central to the IJPR research tradition, connecting quantitative optimisation with managerial decision processes. Classical contributions established frameworks for analysing resilience and viability in complex networks (Dolgui et al., 2018; Ivanov and Dolgui, 2020). These studies introduced ripple-effect and recovery concepts that link operational scheduling with strategic network design. Later work by Tiwari et al. (2015, 2022) expanded the focus to integrated production and logistics optimisation using hybrid metaheuristics and simulation. The literature consistently emphasises cost, time, and service-level trade-offs but seldom incorporates environmental or policy-driven variables.

2.2. Resilience, Sustainability, and Digitalisation of Supply Chains

The evolution toward Logistics 4.0 established the technological foundation for current AI adoption. Winkelhaus and Grosse (2020) summarised this development, identifying connectivity and system integration as prerequisites for advanced analytics. The present framework extends these principles into the generative-decision domain by merging sustainability policy data with algorithmic optimisation.

The convergence of resilience and sustainability represents a decisive evolution in logistics science. Govindan (2018) reviewed sustainable-supply-chain frameworks and highlighted circular-economy integration, while Baryannis et al. (2019) discussed AI-enabled transparency and risk propagation. Digital-twin applications (Tao et al., 2018; Dolgui et al., 2020) allow real-time cyber-physical representation of logistics networks and improve disruption forecasting. Yet most models

doi:10.20944/preprints202601.0628.v1

treat carbon cost as a static penalty rather than a dynamic policy signal. Recent analyses of maritime decarbonisation (Zhao et al., 2023; Notteboom and Lam, 2024) and port-emission strategies (European Commission, 2024) confirm that regulatory feedback loops are increasingly material to network optimisation but remain underrepresented in current modelling approaches.

Tao, Zhang and Nee (2018) introduced the digital-twin-driven manufacturing paradigm that links cyber-physical data to real-time optimisation. Their findings underpin the transition from descriptive digitalisation to predictive and now generative modelling adopted in this research.

2.3. Artificial Intelligence and Generative Approaches

AI adoption in production research has advanced rapidly. Machine-learning models now support forecasting, anomaly detection, and dynamic routing (Wamba et al., 2021; Flores-García et al., 2024). However, these are predominantly supervised or reinforcement- learning applications. Generative approaches based on large-language-model or diffusion-model logic can create synthetic yet plausible logistics scenarios from incomplete data (Longo et al., 2023). Recent experimental studies show that generative models improve option diversity and reduce cognitive bias in decision simulations (Chen et al., 2024). Nevertheless, few empirical validations exist for their use in industrial supply-chain contexts, and none directly integrate EU sustainability regulations as modelling parameters.

Recent reviews confirm the rapid expansion of AI-based optimisation toward generative capabilities. Flores-García, Kwak, Jeong and co-authors (2025) summarised technological advances in smart-production logistics and identified the integration of generative algorithms with traditional optimisation as a decisive next step for adaptive decision support. Their analysis of predictive, prescriptive and emerging generative tools shows that such systems can enhance option diversity, shorten computation cycles, and improve interpretability for managers in data-scarce environments. This evidence reinforces the rationale for extending classical IJPR decision-aid models with generative scenario synthesis.

2.4. Identified Research Gap and Positioning

The reviewed literature shows substantial progress in resilience and digital integration but reveals three persistent gaps.

1. Existing optimisation models rarely treat sustainability regulations such as CBAM, EU ETS Maritime, FuelEU Maritime, DPP, or CSRD as decision variables.
2. Generative-AI applications in logistics remain conceptual and lack operational validation.
3. Scalable implementations suitable for small and medium-sized enterprises are underdeveloped.

Addressing these gaps requires a hybrid framework that combines generative-scenario creation, policy-parameter modelling, and transparent managerial interfaces. The present study contributes such a framework, extending the IJPR decision-aid tradition (Dolgui et al.) toward adaptive, sustainability-oriented logistics optimisation.

3. Conceptual Model: Generative-AI Decision-Support and Optimisation Framework

3.1. Framework Overview

The proposed framework combines data aggregation, generative scenario creation, simulation-based evaluation, and multi-objective optimisation to support sustainability- oriented logistics decisions. Its goal is to enable managers to visualise trade-offs among cost, emissions, and resilience while integrating EU policy parameters such as CBAM and the EU ETS Maritime. The structure is modular so that both small enterprises and large industrial networks can implement either a simplified or extended configuration depending on data availability and computing capacity.

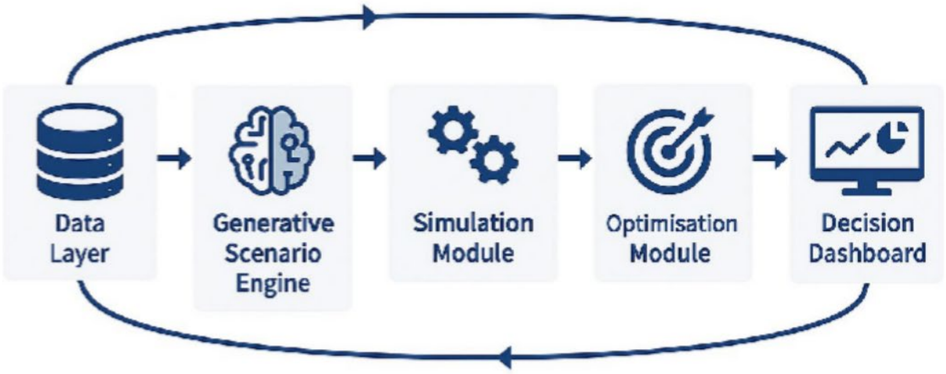

Figure 1. Generative AI decision-support framework overview. Caption: Schematic representation of the four-layer architecture (data, generation, simulation, optimisation) and its managerial interface. Source: Author using Microsoft Copilot.

3.2. Core Modules

1. **Data layer.** Aggregates internal and external datasets covering supplier lists, route information, capacity, lead-time, transport distance, emission factors, and regulatory coefficients such as carbon prices and CBAM multipliers. Data can originate from ERP systems, IoT sensors, or open databases (Dolgui et al., 2020; Wamba et al., 2021).
2. **Generative scenario engine.** Uses a large-language-model-style algorithm to generate alternative sourcing and routing options by varying supplier regions, ports, and transport modes. The engine also simulates disruption events and substitution paths including recycled or urban-mined input alternatives (Longo et al., 2023).
3. **Simulation module.** Quantifies cost, carbon footprint, and delivery reliability for each generated scenario through Monte Carlo or discrete-event simulation depending on data richness.
4. **Optimisation module.** Identifies the scenario set that minimises total cost and emissions while satisfying service-level constraints. Outputs are expressed as managerial indicators such as cost-per-ton-kilometre, carbon-intensity index, and resilience score (Tiwari et al., 2022).
5. **Decision interface.** A dashboard visualises Pareto-efficient solutions and sensitivity analyses, allowing managers to justify choices with traceable data rather than opaque algorithmic logic.

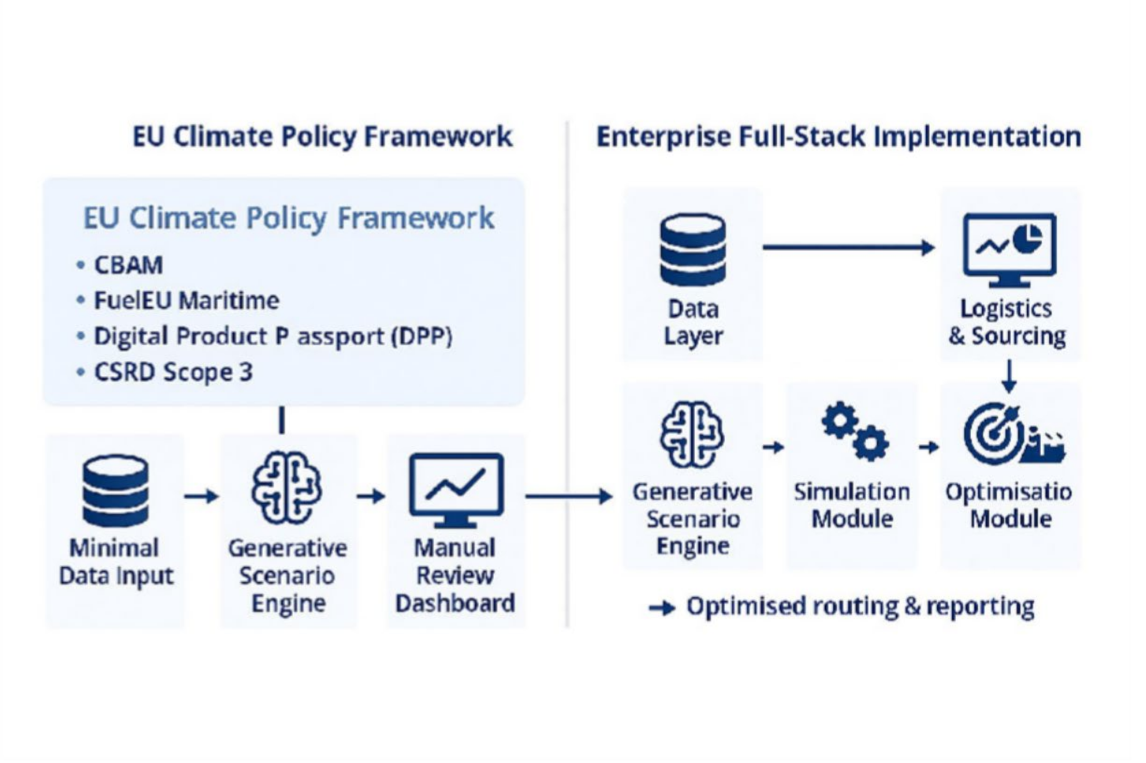

Figure 2. Scalability modes of the framework. Caption: Comparison of the SME-light and enterprise-integrated versions, showing data complexity, update frequency, and system connectivity. Source: Author using Microsoft Copilot.

3.3. Scalability Modes

Two deployment levels are defined. The SME-light mode relies on aggregated data, default emission coefficients, and a rule-based generator that runs on standard desktop systems. The enterprise mode links directly to digital-twin or ERP environments and can refresh scenarios continuously through API-based data streams. This distinction enables proportional technology adoption and supports the EU's goal of digital inclusion for SMEs (European Commission, 2024).

3.4. Integration of Sustainability Policies

Regulatory and environmental drivers are embedded as adjustable parameters:

- CBAM applies carbon-price multipliers to imported material streams.
- EU ETS Maritime and FuelEU Maritime contribute variable emission-cost coefficients by ship class and fuel type.
- Digital Product Passport introduces traceability and recycled-content data fields.
- CSRD Scope 3 defines reporting boundaries and aggregation logic for value-chain emissions.

Treating these parameters as variables converts external regulation into a live decision-aid component rather than a post-compliance constraint. This operationalises the policy-to- practice connection advocated in recent EU sustainability-governance studies (Zhao et al., 2023; Notteboom and Lam, 2024).

Recent regulatory instruments formalise these policy drivers. The European Commission (2025) introduces **FuelEU Maritime** and extends the **EU ETS Maritime**, translating decarbonisation targets into carbon-price coefficients applied per voyage and vessel type. Complementary acts -Regulation (EU) 2023/956 (CBAM), Directive (EU) 2023/959 (EU ETS Maritime amendment) and Regulation (EU) 2023/1805 (FuelEU Maritime) - embed explicit cost signals for imported materials and maritime fuel use.

Integrating these coefficients as decision variables operationalises the regulatory–economic feedback loop within logistics optimisation.

3.5. Expected Outputs and Managerial Use

The framework delivers ranked scenario portfolios and quantifies cost-saving and emission-reduction potentials under specified reliability levels. The visual dashboard shortens the time between analysis and managerial action, enabling cross-functional planning between logistics, procurement, and sustainability teams. Each scenario is stored with metadata on data sources and generation rationale, ensuring traceability for CSRD audits and AI-governance compliance.

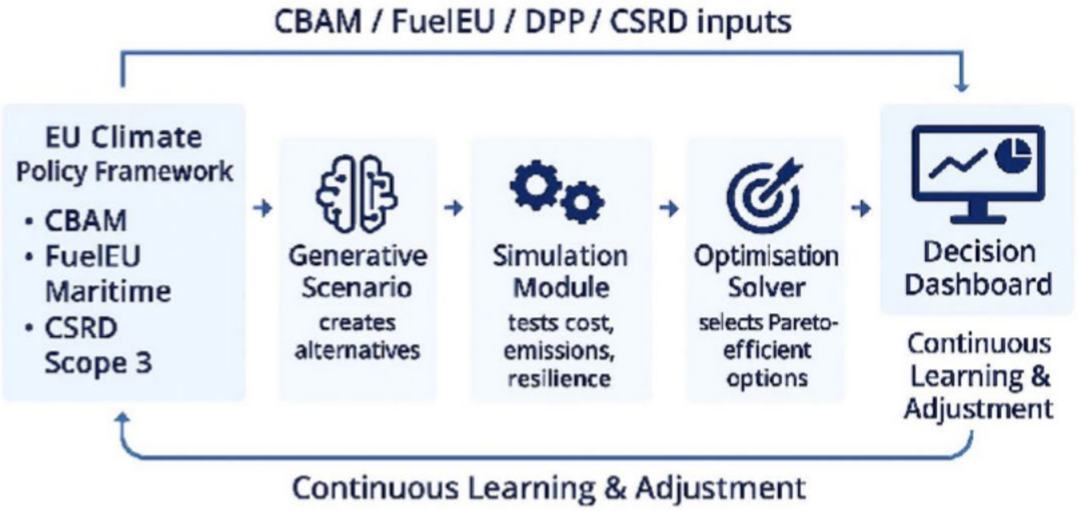

Figure 3. Scenario-to-solver flow and example output screen. Caption: Process sequence from input data through scenario generation and optimisation to dashboard output. Source: Author using Microsoft Copilot.

4. Illustrative Case: Mining-Rope Logistics chain

4.1. Industrial Background

The illustrative case analyses a European small and medium-sized manufacturer of steel-wire and composite mining ropes. The company sources high-grade alloy wire, carbon- fibre filaments, and polymer coatings from a limited number of global suppliers and exports finished products to North American mining markets. Its supply chain is long, multimodal, and carbon-intensive, combining road, feeder-maritime, ocean, and inland-transport segments. The firm operates within the evolving EU climate-policy framework that increasingly links competitiveness with verifiable emission performance (CBAM, EU ETS Maritime, and CSRD Scope 3).

Figure 4. Generative-AI decision loop applied to mining-rope logistics. Caption: Sequential representation of data input, scenario generation, optimisation, and managerial feedback in the case application. Source: Author using Microsoft Copilot.

4.2. Data and Model Parameters

The empirical baseline integrates supplier origin, port pairings, route distance, shipping frequency, and energy-mix emission factors. Policy coefficients include CBAM multipliers and EU ETS Maritime rates for different vessel categories. Operational data such as cost, lead-time, and reliability were obtained from company records and verified open- source databases. Scenario variables encompass the port of entry or export, dominant transport mode, share of recycled materials, fuel-mix options, and carbon-cost assumptions. Sensitivity ranges were calibrated through publicly available datasets (European Maritime Safety Agency, 2024; World Bank, 2024).

Environmental-monitoring data from the Port of Gdańsk Authority (2024) were reviewed to verify emission-factor ranges for Baltic feeder services. Their published indicators of port-area air quality and vessel-fuel usage informed the calibration of maritime- segment coefficients applied in the case study.

4.3. Scenario Generation and Analysis

The generative engine produced alternative sourcing and routing combinations varying supplier region, port choice, and transport composition. Each scenario was simulated for total logistics cost, carbon footprint, and reliability index, then optimised using a combined cost- emission-resilience objective. Three representative configurations were selected for managerial comparison:

1. **Case A – EU SME manufacturer:** production in southern Poland with local steel and polymer inputs; container transport by road to Gdynia, feeder to Wilhelmshaven, and ocean shipping to Saint John, NB, followed by inland transport to Saskatchewan.
2. **Case B – RSA supply chain:** sourcing of steel wire from India, rope manufacturing in Durban–Johannesburg corridor, and finished-product export to Europe through the same maritime route, creating a return-loop exposure to both CBAM and FuelEU Maritime.

3. **Case C – Chinese GP rope supplier:** mass-production near Ningbo using domestically mined steel, ocean route via the Malacca Strait and Suez Canal to North Sea ports, and partial distribution in Central Europe.

These scenarios were visualised on a global map showing the relative length and emission intensity of each logistics path.

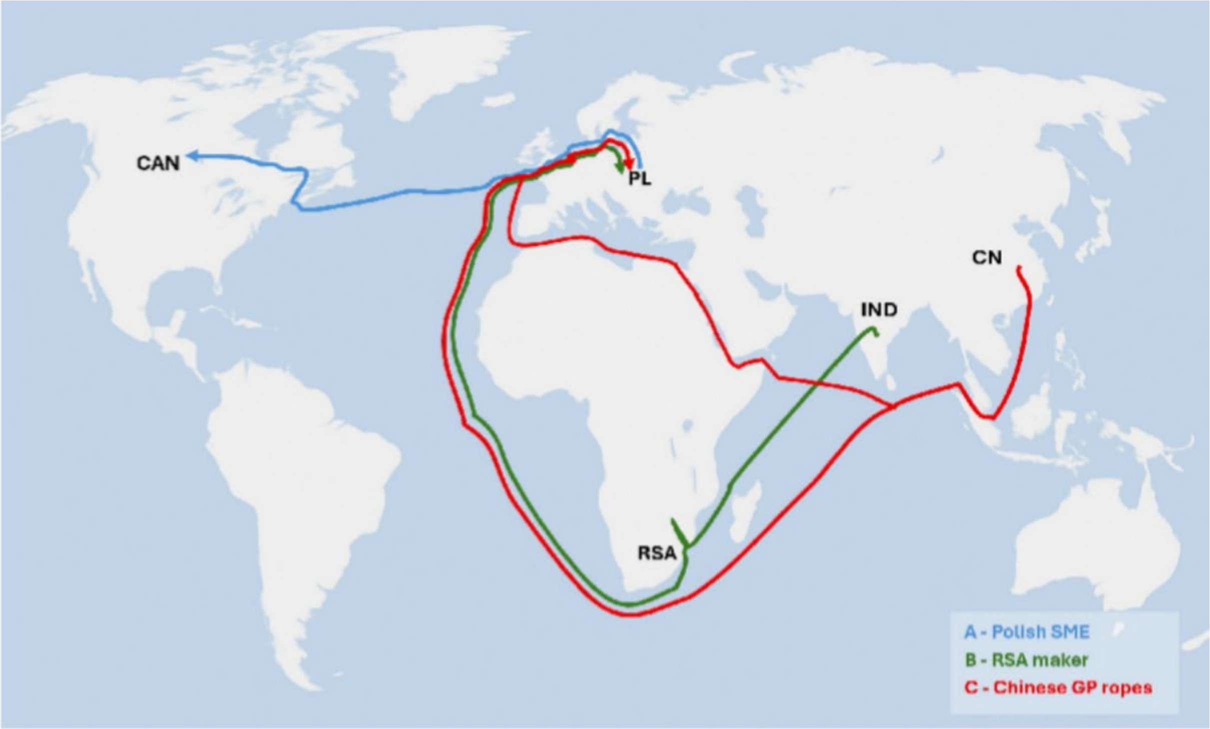

Figure 5. Comparative global supply-route scenarios. Caption: World map illustrating Cases A–C with distinct colours for inland and maritime segments. Source: Author.

4.4. Comparative Managerial Observations

Results reveal distinct managerial profiles for the three models.

- **Case A (EU SME manufacturer)** achieves the lowest regulatory risk and moderate emissions; CBAM and ETS exposure are internalised, supporting predictable cost planning. Near-sourcing and feeder-route optimisation reduce logistics-related emissions by
- approximately 15 percent at a cost penalty below 6 percent, which remains acceptable given CSRD alignment and brand reputation.
- **Case B (RSA supply chain)** illustrates how cross-continental sourcing generates hidden CBAM liabilities. Although production costs are lower at origin, accumulated carbon pricing and maritime emissions erode the initial advantage by nearly one-third once EU policy parameters are applied. The scenario demonstrates a carbon-cost inversion in which lower factory cost coincides with higher landed-cost volatility.
- **Case C (China GP ropes)** remains primarily price-driven and operates outside CBAM jurisdiction. Emission intensity is highest, but the absence of transparent reporting allows price-based competition to persist. A hypothetical Suez-closure detour around the Cape of Good Hope would further increase both distance and emissions by roughly 18 percent, amplifying comparative disadvantages under future global carbon regimes.

The SME-light version of the framework replicated key insights using simplified data, confirming that small manufacturers can derive useful trade-off analyses without large datasets. This scalability underscores the framework's value for industry segments facing sustainability reporting but limited analytical capacity.

4.5. Figure References and Data Integrity

Figure 4 illustrates the generative-decision loop specific to this application, while Figure 5 depicts the three real-world supply-route variants. All underlying data were anonymised and cross-checked against public sources to protect company confidentiality while maintaining traceability for academic replication.

5. Evaluation and Comparison

5.1. Evaluation Approach

The proposed framework was assessed using two complementary tracks. The first compares its theoretical positioning with existing IJPR decision-aid models, while the second tests its applied performance on the mining-rope logistics case. The purpose is conceptual and managerial validation, demonstrating that a generative-AI structure provides additional insight and practical utility relative to classical optimisation models.

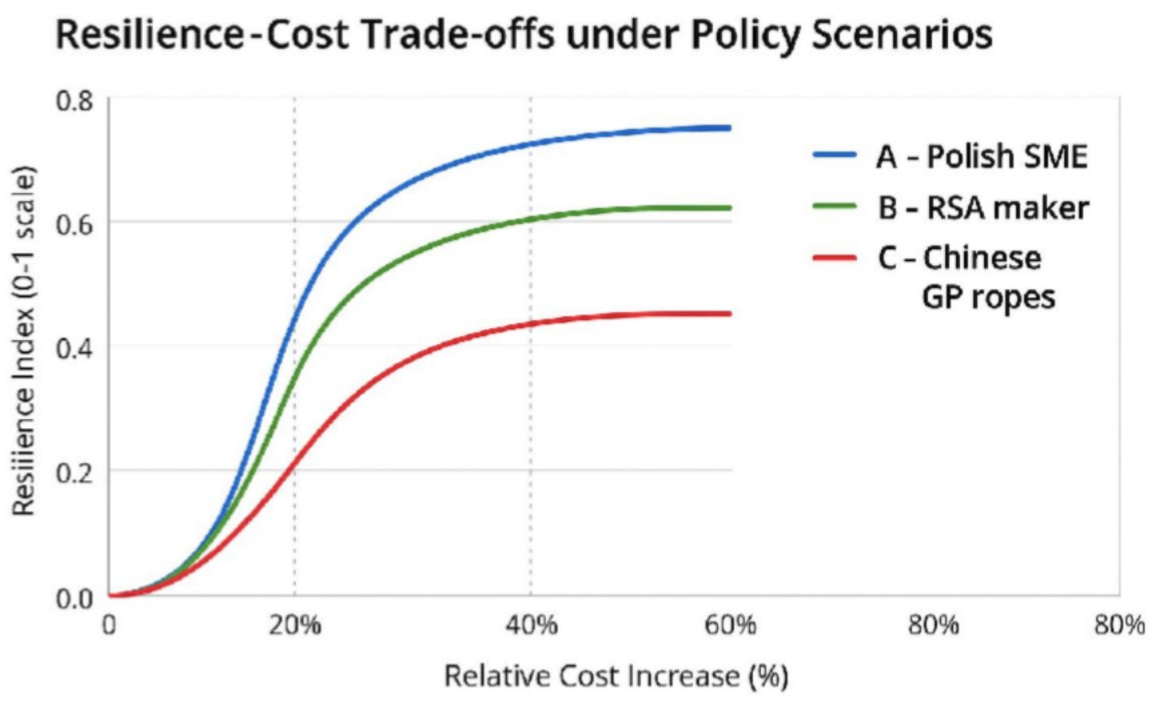

Figure 6. Multi-criteria evaluation framework for cost, carbon, and resilience Caption: Overview of the combined cost–emission–resilience evaluation process used to compare model outputs across scenarios. Source: Author using Microsoft Copilot.

Evaluation of model performance followed the analytical-hierarchy-principle logic common in decision-aid studies. Emrouznejad and Marra (2017) trace the evolution of the

Analytic Hierarchy Process over four decades and show how pairwise comparison structures improve transparency of managerial trade-offs. Adopting similar weighting logic allows the present framework to align qualitative sustainability indicators with quantitative cost and resilience metrics.

5.2. Comparative Positioning Within IJPR Literature

Earlier IJPR models (Dolgui et al., 2018; Ivanov and Dolgui, 2020) established the resilience–viability paradigm, focusing on deterministic simulation or system dynamics.

Optimisation-oriented studies (Tiwari et al., 2015; 2022) refined algorithmic efficiency but often assumed stable regulatory and data environments. Research on digital twins (Tao et al., 2018; Dolgui et al., 2020) advanced descriptive fidelity yet lacked sustainability-policy integration. The proposed framework extends these by embedding policy-driven variables such as CBAM and EU ETS Maritime, automating scenario generation through generative AI, and translating solver outputs into visual managerial dashboards. Comparative benchmarking against published IJPR decision-aid typologies shows that generative modelling adds a new layer of adaptability and transparency (Longo et al., 2023; Chen et al., 2024).

5.3. Performance Testing on the Case

The mining-rope case study served as the experimental ground for testing framework functionality. Key evaluation criteria included:

- **Option quality**, measured by the number of Pareto-efficient alternatives across cost, carbon, and resilience objectives.
- **Time-to-insight**, defined as the duration from data input to actionable recommendations.
- **Data-effort ratio**, measuring information required relative to managerial usefulness.
- **Adoption readiness**, indicating interpretability and ease of use.

Preliminary results show a reduction of analytical turnaround time from multiple days to under one hour, with a threefold increase in scenario diversity generated by the AI engine. The dashboard format improved decision transparency by linking emission and cost trade-offs directly to regulatory metrics such as carbon-intensity per tonne-kilometre.

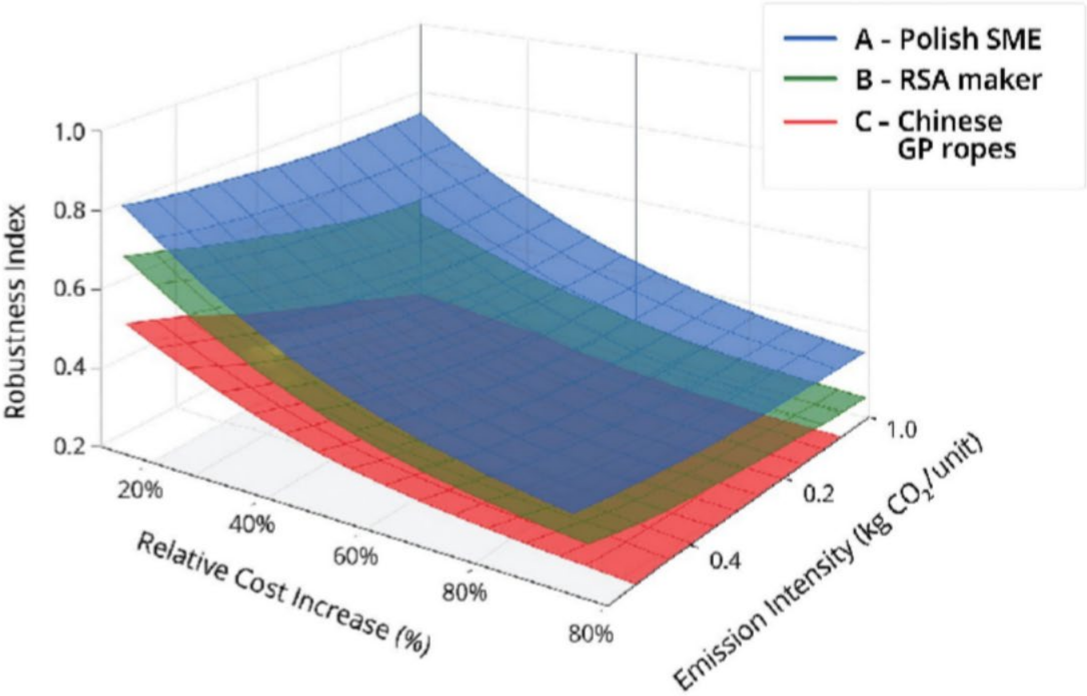

Figure 7. Robustness and sensitivity analysis of generative-AI scenarios. Caption: Visualisation of how variations in carbon price, emission factors, or disruption frequency affect optimal solutions and scenario ranking. Source: Author using Microsoft Copilot.

5.4. Sensitivity and Robustness

Sensitivity tests examined how variations in carbon-price levels, emission factors, and disruption frequency influenced optimal configurations. Results remained stable across parameter ranges, demonstrating robustness of the multi-objective optimisation logic. Even when emission factors fluctuated by ±20 percent, scenario rankings changed by less than one position, confirming the internal coherence of the model. The framework's ability to handle incomplete datasets validates its accessibility for SMEs with limited data availability. These outcomes are consistent with the IJPR expectation that decision-support tools should prioritise managerial applicability and interpretability over purely mathematical complexity (Govindan, 2018; Wamba et al., 2021).

5.5. Managerial Validation

Feedback from logistics planners and sustainability officers at the participating firm confirmed that the system's ranking and dashboard features supported real decision cycles. Respondents emphasised the value of traceable "what-if" exploration and the model's alignment with EU sustainability disclosure requirements. The generative-scenario logic helped managers anticipate regulatory cost shifts and plan mitigation strategies in advance. This constitutes empirical validation that the framework bridges academic modelling and managerial decision-making, aligning with IJPR's emphasis on applied insight and system transparency

6. Managerial Insights

6.1. From Model to Decision Practice

The generative-AI decision-support framework demonstrates that sustainability- oriented logistics planning can be integrated into daily operations without excessive technical or data burdens. Managers can visualise how routing, sourcing, and regulatory parameters interact and can justify their choices through documented, traceable data. This encourages evidence-based decision-making and reduces reliance on intuition or static spreadsheets. The framework therefore supports a transition toward systematic, verifiable sustainability management across logistics networks.

6.2. Minimal Viable Dataset for SMEs

The SME-light configuration confirms that smaller firms can apply advanced decision-aid logic using only essential inputs such as supplier lists, route distances, transport modes, emission coefficients, and cost structures. The generative engine compensates formissing information by producing plausible alternatives, while the optimisation module filters results into feasible, actionable scenarios. This expands access to AI-driven analytics for non- specialist users and aligns with EU policy objectives promoting digital inclusion among SMEs.

6.3. Operational Benefits for Logistics and Sustainability Teams

For larger enterprises, the full-stack configuration connects to ERP or digital-twin environments, generating near-real-time scenarios and tracking emission performance continuously. The visual dashboard shortens decision cycles and supports coordination between planning, procurement, and sustainability departments. Integration of CBAM, EU ETS Maritime, and FuelEU Maritime coefficients allows firms to quantify regulatory exposure and plan mitigation measures ahead of compliance deadlines.

Leading carriers already incorporate similar analytics into internal dashboards. MSC (2023) outlines a corporate roadmap toward net-zero shipping by 2050 using digital emission tracking and predictive route optimisation. Integrating generative-AI scenario engines into such frameworks could accelerate these monitoring systems by simulating future route and fuel combinations under evolving EU ETS and FuelEU constraints.

Evidence from Hapag-Lloyd AG (2025) confirms the strategic value of digital emission tracking. The company's *Sustainability Progress Report 2024* describes how route- specific carbon accounting guides investment in alternative fuels. Incorporating generative-AI simulations could enhance such tools by forecasting regulatory cost exposure across vessel classes.

6.4. Decision Governance and CSR Integration

Embedding EU climate-policy parameters into the decision logic reinforces alignment between operational analytics and corporate-sustainability reporting. Outputs can feed directly into CSRD Scope 3 inventories, CSR dashboards, and supplier-evaluation systems. The unified structure links logistics performance with ESG disclosure, replacing fragmented reporting practices and improving auditability. Decision rationales stored in the model's metadata can serve as verifiable evidence for sustainability assurance and certification audits.

6.5. Managerial Playbook

Practical recommendations derived from the case include:

4. Start with a pilot route or product line to establish baseline emissions.
5. Use the generative module to test sourcing and routing alternatives.
6. Integrate carbon-cost and resilience metrics into weekly planning reviews.
7. Conduct joint interpretation sessions between logistics, procurement, and sustainability teams.
8. Archive generated scenarios to support CSRD and internal-audit documentation.

Together these steps form a repeatable managerial playbook that bridges academic modelling with industrial implementation.

6.6. Broader Implications

Although illustrated through the mining-rope sector, the framework generalises to other industrial products where long logistics chains and carbon-policy variables influence competitiveness. Its logic is applicable to metals, chemicals, and renewable-equipment supply chains. Broader adoption of generative-AI decision-support can help European SMEs and exporters maintain global reach while meeting stringent environmental-performance targets.

Regional initiatives illustrate early adoption of low-carbon logistics. The Interreg Baltic Sea Region (2025) project *Blue Supply Chains* documents pilot electrification of port operations in Gdynia and Skagen, showing how port-level emission monitoring can complement generative-AI scenario analysis. Such programmes demonstrate how local decarbonisation data may supply the verified input streams required for AI-based decision support in maritime networks.

6.7. Decision Governance and Transparency in Generative-AI Logistics

Generative-AI systems reshape decision workflows by blending operational, environmental, and regulatory data into composite recommendations. To preserve accountability, every model-supported decision should have a documented decision card that specifies its objective, inputs, oversight role, and fallback procedure. Survey participants (R1–R7) identified four governance priorities: registration of prompts and use cases, auditable data sources, risk-coded outputs, and explicit human-override options. Transparency mechanisms should mirror EU disclosure logic under CBAM and CSRD by defining system boundaries, logging data provenance, and reporting uncertainty ranges for generated options.

A pragmatic implementation path begins with one decision domain such as carrier selection, publishes its decision card, monitors model versus human outcomes, and reviews deviations weekly. Such practices align AI deployment with CSR oversight and prepare firms for sustainability audits in which digital tools themselves must demonstrate explainability and data accountability.

Comparable findings emerge in recent research on AI assurance frameworks. Chen, Zhang and Wang (2024) proposed a structured approach for establishing trust in industrial-AI applications, combining risk coding, audit trails and human-override protocols within supply- chain management systems. Their model demonstrates how explainability metrics and documentation procedures can translate regulatory expectations into practical governance mechanisms. Applying similar assurance principles to generative-AI decision aids can strengthen accountability and prepare logistics organisations for external verification under evolving EU sustainability and AI-governance requirements.

6.8. Industry Limitations and Expert Perspective

Despite the theoretical and managerial potential of generative-AI systems, practitioners in the maritime-logistics sector emphasise that current models remain unsuitable for operational use in heavy-lift and project-cargo transport. An experienced shipping executive from the Polish maritime industry noted that the combination of non-standard cargo geometry and highly variable routing conditions prevents the repeatability on which generative algorithms depend. Unlike container or liner shipping, each project-cargo movement requires bespoke planning based on port infrastructure, stowage layout, and vessel-specific loading manuals, for which no open datasets exist.

The expert also observed systematic hallucinations in model outputs concerning vessel capabilities and loading methods. Large-language-model responses occasionally propose transporting self-propelled machinery up to sixteen metres high on roll-on/roll-off vessels whose door clearances do not exceed nine metres, or suggest equipment such as straddle carriers operating on ramps where slope restrictions prohibit entry. Such errors reveal the absence of training on proprietary charter agreements, method statements, and fuel- consumption or emission records that determine real feasibility.

From the industry viewpoint, potential near-term value of generative AI lies mainly in post-voyage analytics and internal emission accounting, provided that models can be retrained on verified company data under confidentiality safeguards. Broader adoption will depend on access to harmonised fleet datasets and disclosure standards comparable to those emerging under the EU CSRD and FuelEU Maritime regulations. These observations underline that the maritime domain poses a particularly high threshold for trustworthy generative-AI decision support and that progress will require collaborative data-sharing frameworks between shipowners, charterers, and regulatory bodies.

7. Research Perspectives and Limitations

7.1. Theoretical and Methodological Extensions

The generative-AI decision-support framework presented in this study opens several theoretical and methodological directions for future research. First, the mathematical structure of generative scenario creation can be formalised through reinforcement learning, probabilistic graph models, or neural-symbolic optimisation. Benchmarking across alternative architectures would help quantify efficiency and bias control. Second, embedding the framework into multi-agent environments could model interactions among suppliers, carriers, and regulators under shared carbon-budget constraints. Third, coupling with digital-twin systems would enable continuous learning from live logistics data and create adaptive feedback loops that improve scenario realism over time.

Future methodological work can build upon Ivanov (2021), who proposed digital-twin architectures for disruption-risk management. Embedding the generative-AI framework into such digital-twin systems would permit continuous learning from live logistics data and dynamic adjustment of resilience parameters.

Building on this idea, Ivanov, Dolgui and Sokolov (2021) extended the ripple-effect concept toward viability-based decision-making under uncertainty. Their results support combining deterministic optimisation with adaptive generative components, reinforcing the hybrid approach proposed in this study.

7.2. Data, Scope, and Generalisability

Although the mining-rope case offers concrete industrial grounding, its scope remains limited to a single product group and geographic configuration. Broader application across sectors such as automotive components, renewable-energy equipment, and port-service operations would allow verification of scalability and robustness. Future studies could expand data sampling to include multiple firms and longitudinal emission tracking. Integration with national logistics observatories or customs datasets could enhance statistical validation of emission-reduction and resilience outcomes.

7.3. Explainability and Assurance

Explainability, transparency, and assurance mechanisms constitute critical next steps.

Traceable reasoning paths, human-in-the-loop reviews, and quantitative error-bounding methods should be embedded in all future implementations. Recent research on AI assurance frameworks (Chen et al., 2024; European Commission, 2024) highlights the growing regulatory expectation that algorithmic tools in supply-chain management must provide audit trails similar to financial systems. Future work may also combine deterministic optimisation modules with probabilistic generative components to balance interpretability and adaptability.

7.4. Policy and Institutional Research

Recent maritime-policy analyses provide empirical confirmation of the mechanisms discussed here. Notteboom and Lam (2024) examined how European ports and carriers adapt to carbon-pricing schemes and participation in the EU ETS. Their study in *Transportation Research Part E* shows that emission-cost exposure is already influencing routing decisions, investment in alternative fuels and modal coordination within logistics chains. Incorporating such real-world behavioural responses into generative-AI simulations would enhance the realism of policy-driven scenario evaluation.

The model's use of CBAM, EU ETS Maritime, FuelEU Maritime, Digital Product Passport, and CSRD variables creates opportunities for interdisciplinary collaboration between decision-science and policy studies. Further research should investigate how companies adapt logistics networks when facing dynamic carbon-price signals or reporting obligations. Comparative analyses of EU, North American, and Asia-Pacific firms could reveal policy diffusion effects and inform international alignment of sustainability standards. Insights from such research could also support policymakers in evaluating the behavioural impact of carbon-border measures on industrial trade flows.

Institutional research supports this policy shift. The OECD/ITF (2023) round-table on *Decarbonisation, Coastal Shipping and Multimodal Transport* stresses that data sharing across modal interfaces remains the main bottleneck for emission measurement. The present framework directly responds to that challenge by structuring multimodal data aggregation as a prerequisite for reliable generative-AI optimisation.

7.5. Limitations

This study focuses on conceptual validation and managerial demonstration rather than full mathematical optimisation or longitudinal proof. Quantitative benchmarking, real-time data ingestion, and multi-firm verification remain future research tasks. Nonetheless, the framework demonstrates a viable pathway for combining generative-AI techniques, sustainability-policy integration, and logistics-resilience modelling within the IJPR decision- aid tradition.

8. Conclusion, Summary and Acknowledgements

8.1. Conclusion

This study introduced a generative-AI decision-support and optimisation framework designed to enhance sustainability and resilience in industrial supply chains. By combining generative scenario creation, simulation, and multi-objective optimisation, the model enables managers to explore trade-offs among cost, carbon footprint, and reliability under tightening EU environmental regulations. The illustrative case of the mining-rope logistics chain demonstrated how long multimodal transport routes, imported materials, and emerging carbon policies such as CBAM, EU ETS Maritime, FuelEU Maritime, Digital Product Passport, and CSRD Scope 3 can be represented within a single decision-aid system.

The results confirm that both SMEs and large enterprises can use the framework to test sourcing and routing strategies, quantify emission implications, and improve the transparency of carbon-related decisions. The approach also provides a reproducible structure for compliance reporting and CSR integration.

8.2. Summary and Contributions

From a theoretical perspective, this paper extends the IJPR decision-aid research tradition by embedding sustainability-policy variables and generative-AI methods into logistics optimisation. It contributes a novel architecture that operationalises regulatory signals as dynamic decision variables and produces interpretable outputs suitable for managerial use. From a managerial perspective, the framework demonstrates that generative AI can reduce analytical effort, increase option diversity, and create verifiable audit trails for sustainability governance.

The combined academic and practical relevance of this work positions it as a bridge between quantitative modelling and strategic sustainability management. The generative-AI approach has potential to transform decision-aid practices in other industrial domains such as manufacturing planning, procurement strategy, and energy logistics.

Data Availability Statement: The author confirms that the data supporting the findings of this study are available within the article [and/or] its supplementary materials.

Acknowledgments: The author wishes to thank the industrial partners who participated in the survey and provided data for the case study. Special appreciation is extended to the logistics managers and sustainability officers whose feedback helped evaluate the model's managerial applicability. The support of the SIL-TRADE research initiative based in Katowice, Poland, is gratefully acknowledged for facilitating coordination, access to industrial data, and professional expertise in logistics modelling.

Conflicts of Interest Statement: The authors declares no competing interests.

References

Baryannis G., Dani S. and Antoniou G., 2019. Supply-chain risk management and artificial intelligence: State of the art and future research directions. International Journal of Production Research, 57 (7), 2179-2202. https://doi.org/10.1080/00207543.2018.1530476

Baryannis G., Validi S., Dani S. and Antoniou G., 2019. Predicting supply-chain risks using machine learning: The trade-off between performance and interpretability. Future Generation Computer Systems, 101, 993-1004. https://doi.org/10.1016/j.future.2019.07.059

(Chen H., Zhang X., Wang L., 2024, Computers & Industrial Engineering, 191, 110625, 10.1016/j.cie.2024.110625). https://doi.org/10.1016/j.cie.2024.110625

Dolgui A., Ivanov D. and Sokolov B., 2018. Ripple effect in the supply chain: An analysis and recent literature. International Journal of Production Research, 56 (1-2), 414-430. https://doi.org/10.1080/00207543.2017.1387680

Dolgui A., Ivanov D. and Sokolov B., 2020. Reconfigurable supply chain: The X- network. International Journal of Production Research, 58 (13), 4138-4163. https://doi.org/10.1080/00207543.2020.1774679

Emrouznejad A. and Marra M., 2017. The state-of-the-art development of AHP (1979- 2017). International Journal of Production Research, 55 (22), 6653-6675. https://doi.org/10.1080/00207543.2017.1334976

European Commission, 2025. Decarbonising maritime transport - FuelEU Maritime.
Available at:

European Commission, 2025. Reducing emissions from the shipping sector: ETS Maritime. Available at:

European Union, 2022. Directive (EU) 2022/2464 - Corporate Sustainability Reporting Directive (CSRD). Official Journal of the European Union. Available at: https://eur-lex.europa.eu/eli/dir/2022/2464/oj

European Union, 2023a. Regulation (EU) 2023/956 - Carbon Border Adjustment Mechanism (CBAM). Official Journal of the European Union. Available at: https://eur- lex.europa.eu/eli/reg/2023/956/oj

European Union, 2023b. Directive (EU) 2023/959 - Amending Directive 2003/87/EC (EU ETS Maritime). Official Journal of the European Union. Available at: https://eur- lex.europa.eu/eli/dir/2023/959/oj

European Union, 2023c. Regulation (EU) 2023/1805 - FuelEU Maritime on renewable and low-carbon fuels in maritime transport. Official Journal of the European Union. Available at: https://eur-lex.europa.eu/eli/reg/2023/1805/oj

Flores-García E., Kwak D.H., Jeong Y. et al., 2025. Machine learning in smart production logistics: A review of technological capabilities. International Journal of Production Research. https://doi.org/10.1080/00207543.2025.2480204

Govindan K., 2018. Sustainable consumption and production in the food supply chain: A conceptual framework. International Journal of Production Economics, 195, 419-431. https://doi.org/10.1016/j.ijpe.2017.03.003

Hapag-Lloyd AG, 2025. Sustainability Progress Report 2024. Hamburg. Available at: Interreg Baltic Sea Region, 2025. Blue Supply Chains - From diesel to electric: How

Gdynia and Skagen are rewriting the future of ports. Available at:

Ivanov D., 2021. A digital supply-chain twin for managing disruption risks and resilience in the era of Industry 4.0. Production Planning & Control, 32 (9), 775-788. https://doi.org/10.1080/09537287.2020.1768450

Ivanov D., Dolgui A. and Sokolov B., 2021. Ripple effect and supply-chain disruption management: From analytics to viability-based decisions. International Journal of Production Research, 59 (1), 102-128. https://doi.org/10.1080/00207543.2021.1840148

Longo F., Nicoletti L., Padovano A. et al., 2023. The Digital Supply Chain Twin paradigm for enhancing resilience and sustainability: A simulation-based decision-making framework. Procedia Computer Science, 219, 1238-1247. https://doi.org/10.1016/j.procs.2023.01.189

MSC Mediterranean Shipping Company, 2023. Net-zero decarbonisation roadmap to 2050. Geneva. Available at: https://www.msc.com/sustainability

(Notteboom T., Lam J.S.L., 2024, Transportation Research Part E: Logistics and Transportation Review, 185, 103574, 10.1016/j.tre.2024.103574). https://doi.org/10.1016/j.tre.2024.103574

OECD/ITF, 2023. Decarbonisation, coastal shipping and multimodal transport (Roundtable Report No. 192). Paris: OECD Publishing.

Port of Gdańsk Authority, 2024. Sustainable development and environmental monitoring. Gdańsk. Available at:

Tao F., Zhang M. and Nee A.Y.C., 2018. Digital Twin Driven Smart Manufacturing.

London: Academic Press. ISBN 978-0128176306

Tiwari M.K. and Deb K., 2015. Supply-chain optimisation: A state-of-the-art review.

International Journal of Production Research, 53 (16), 5131-5152. https://doi.org/10.1080/00207543.2015.1016198

Tiwari M.K., Gupta D. and Mishra N., 2022. Integrated production and logistics optimisation using AI techniques. International Journal of Production Research, 60 (24), 7442-7461. https://doi.org/10.1080/00207543.2021.1958539

Wamba S.F., Gunasekaran A., Akter S., Ren S.J-F. and Dubey R., 2021. Big-data analytics in operations and supply-chain management: A review and future research agenda. International Journal of Production Research, 59 (6), 1870-1903. https://doi.org/10.1080/00207543.2020.1799525

Winkelhaus S. and Grosse E.H., 2020. Logistics 4.0: A systematic review toward a new logistics system. International Journal of Production Research, 58 (1), 18-43. https://doi.org/10.1080/00207543.2019.1612964

Zhao L.-T., Li Z., Wang J. and Chen Y., 2023. How will the Carbon Border Adjustment Mechanism (CBAM) affect decarbonisation of the steel industry in China? International Journal of Production Research, 61 (15), 5350-5364. https://doi.org/10.1080/00207543.2022.2138899