Multi-Scale Supply-Chain Intelligence through AI, FKF Spectral Analysis, and Quantum Optimization

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How to Cite this Article:

S, S. & M, S. S. (2026). Multi-Scale Supply-Chain Intelligence through AI, FKF Spectral Analysis, and Quantum Optimization. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(8), 1-9. https://doi.org/10.55041/ijcope.v2i8.281

https://doi.org/10.55041/ijcope.v2i8.281

Abstract—
Global supply chains now fail in coupled ways: demand shocks travel with lead-time resonance, cyber events travel with physical delays, and energy-system constraints travel with freight capacity. Artificial intelligence is widely proposed as the instrument that turns those couplings into forecasts and then into mitigation. This paper reconstructs a systematic-style review, a conceptual framework, and a research agenda from a closed corpus of twenty-five publications spanning digital twins, green logistics analytics, blockchain enabled transparency, Industry 5.0, IoT–AI–quantum convergence, quantum annealing for disruption, spectral and distributional transforms of multi-echelon dynamics, and adjacent work on electric-mobility energy systems and infrastructure security. The synthesis organizes AI contributions along the four classical supply-chain risk-management stages identification, assessment, mitigation, and monitoring and overlays three enabling layers: (i) sensing and human machine interaction, (ii) computational intelligence including quantum and spectral methods, and (iii) energy-and-infrastructure constraints that make logistics risk material.

Keywords— supply chain risk management; supply chain resilience; artificial intelligence; digital twin; FKF transform; FKL transform; spectral analysis; multi-echelon lead time; quantum optimization; quantum annealing; blockchain traceability; Industry 5.0; Internet of Things; green logistics; electric mobility

I. INTRODUCTION

Supply-chain risk management (SCRM) matured as a managerial discipline around identification, assessment, mitigation, and monitoring. That four-stage grammar remains useful, but the objects inside it have changed. Risks are no longer only local stockouts or single-node failures. They are multi-scale oscillations in lead time [7], [8], [9], correlated supplier defaults, cyber-physical attacks on logistics infrastructure [3], [17], battery and energy bottlenecks in electrified fleets [6], [16], [18], [20], [22], and policy shocks that rewire trade graphs. Prediction therefore cannot be a single-horizon forecast. Mitigation cannot be a static buffer policy.

Artificial intelligence entered this setting first as demand forecasting and supplier scoring, then as text mining of disruption news, then as reinforcement learning for inventory and routing, and more recently as generative and agentic systems that draft contingency plans. Parallel digital technologies Internet of Things sensing [14], [20], blockchain provenance [3], digital twins [1], and experimental quantum optimization [5], [19], [21] have been argued to enlarge what AI can see and what it can prescribe. A separate mathematical line has treated supply-chain time series as spectral objects, using the FKF and FKL transforms and their distributional extensions to extract resonances, time shifts, and secure modulation features from multi-echelon lead times [9]-[13], [24], [25].

This reconstruction asks four questions of that corpus:

How is AI currently used across the four SCRM stages when the evidence base is restricted to this digital–spectral–quantum programme?

Which enabling technologies (digital twins, blockchain, IoT, quantum, spectral transforms, energy systems) actually change prediction or mitigation rather than merely accompanying them?

What conceptual architecture links multi-scale detection to human-centric response?

Where should the next wave of empirical and methodological work concentrate?

The contribution is threefold. First, the paper maps the twenty-five works onto SCRM stages and risk classes instead of listing technologies in isolation. Second, it proposes the Predict–Mitigate framework: a closed loop in which spectral and learning models produce early-warning features, digital twins [1] and quantum/classical optimizers [5], [19], [21] generate responses, blockchain [3] and operator interfaces [4], [15] constrain those responses, and monitoring feeds residuals back into the transforms. Third, it states a research agenda that is honest about maturity: digital twins and AI analytics are nearer to practice [1], [15], [23] than quantum annealing [5], [19], [21] or specialized integral transforms [7]-[13], [24], [25].

II. SUPPLY-CHAIN RISK, RESILIENCE, AND PREDICTION

Risk in a supply network is the possibility that a flow material, information, or finance—deviates enough to damage service or cost. Resilience is the capability to prepare, absorb, recover, and adapt. Prediction is the statistical or algorithmic attempt to estimate the onset, magnitude, duration, or cascade path of such deviations before they fully materialize. Mitigation is the set of actions that change exposure or consequence: dual sourcing, inventory repositioning, mode shifting, contract renegotiation, cybersecurity containment, and, increasingly, automated re-planning.

Digital transformation reviews have already argued that visibility, analytics, automation, and connectivity are the capabilities through which technologies become resilience [23]. The present paper takes that claim as a starting point and asks a narrower question: which AI and adjacent methods improve the prediction–mitigation couple, not merely post-hoc description.

A closed-corpus reconstruction

Open SLRs of AI-SCRM typically draw dozens of papers from Scopus and Web of Science and classify them by algorithm and SCRM stage. That design is valuable and is not reproduced here. The commissioning task was to reconstruct a review that uses a specified authorial corpus. The methodological stance is therefore integrative rather than exhaustive: the corpus is treated as a research programme with several strands, and the review's job is to make the programme internally coherent and to mark where it does not yet meet the standards of a field-level SLR.

Strands inside the corpus

Six strands are distinguishable.

Digital and cyber-physical resilience: digital twins for adaptive global chains [1]; AI–blockchain transparency and traceability [3]; digital-transformation SLR [23].

Sustainable and green intelligence: bibliometric mapping of AI in sustainable logistics [2]; Industry 5.0 human-centric automation [15].

Convergent computing: IoT, AI, and quantum computing as a stacked logistics architecture [14]; quantum opportunities in SCM [5], transportation [21], and unit-load-device annealing under disruption [19].

Spectral dynamics: FKF/FKL transforms, time-shift and modulation properties, distributional extensions, and sequential convergence, applied to multi-echelon lead times and resilience signals [7]-[11], [12], [13], [24], [25].

Energy-mobility constraints: battery materials and management [6], plug-in hybrid battery sizing [18], solar-assisted architectures [16], [22], and intelligent transportation trends [20]. These papers are not SCRM studies; they specify physical constraints that AI risk models must respect when fleets electrify.

Sensing, control, and infrastructure security: swipe-based human–machine control [4] and power-line-carrier anti-theft communication [17]. These are early engineering works. They are cited only as precursors of operator interfaces and infrastructure-integrity monitoring two inputs any AI risk system still needs.

The spectral behavior of the K-type kernel can be characterized through a second-order differential operator of the form

$$\boldsymbol{\mathcal{L}_r K_{i\lambda}(r) = -\left(\lambda^2 + \frac{1}{4}\right) K_{i\lambda}(r)},$$

where represents the corresponding radial differential operator [7], [11].

III. SYNTHESIS BY SCRM STAGE

The FKF spectral representation, where $\boldsymbol{e}$indexes the supply-chain echelon , $\boldsymbol{x_e(t)}$ multi-echelon lead-time signal can be expressed as

$\boldsymbol{X_e(\omega, \lambda) = \mathcal{F}_{FKF}\{x_e\}(\omega, \lambda)}$,

where represents temporal frequency and denotes the positive spectral scale parameter.. Changes in $\boldsymbol{X_e(\omega, \lambda)}$indicate whether an operational disturbance bottlenecks can generate broader or high-frequency spectral components [7], [8], [9], [10].

Identification: seeing the risk before it is named

Identification is the conversion of raw telemetry and text into a recognized risk object. In the digital strand, IoT and intelligent transportation systems supply the streams [14], [20]; blockchain and AI jointly reduce the chance that the stream is forged or incomplete [3]; and infrastructure-oriented sensing, historically illustrated by power-line-carrier integrity monitoring

[17], remains a reminder that physical assets still disappear or are tampered with.

The distinctive claim of the spectral strand is that many supply-chain risks are not events first and time series second; they are resonances and shifts in multi-echelon flows. Multi-scale spectral analysis and residue-based resonance extraction are proposed as ways to find hidden periodic stress in hybrid-vehicle and logistics systems [7]. Shift-invariant FKF analysis of lead times is intended to keep those features stable when a disruption merely delays a pattern rather than changing its shape [8], [12]. A broader FKF resilience framework treats the transform output as a monitoring signature rather than a one-off diagnostic [9]. The FKL variant offers an alternative kernel for the same class of series [11]. Distributional and sequential-convergence results are the mathematical licence for applying those transforms to the irregular, heavy-tailed series that real disruption data produce [24], [25].

Green-AI bibliometrics [2] add a different identification problem: environmental and regulatory risks are under-indexed if models are trained only on cost and service labels. Identification, in other words, is as much a question of which loss function the organization chooses as of which detector it trains.

Assessment: from signal to severity and cascade

Assessment estimates probability, impact, and propagation. Digital twins are the corpus's primary instrument for this stage because they allow counterfactual loading of a network that has not yet failed [1]. The digital-transformation SLR reports that digitally mature organizations claim substantially faster recovery and that predictive analytics can lift forecasting accuracy, while also warning that measurement remains inconsistent across studies [23].

Spectral differential properties of the distributional FKF transform are offered as a way to ask how a small change in a lead-time distribution moves the resilience signature [10], [24]. That is an assessment idea: not only "is there a resonance?" but "how brittle is the resonance to a further shock?" Energy-system papers enter here as binding constraints rather than as algorithms. Battery chemistry, management systems, and sizing rules determine how much mobility capacity remains after a grid or charging disruption [6], [18]. Solar-assisted and hybrid architectures change the same constraint set by adding on-board generation [16], [22]. An AI risk model that ignores those constraints will overstate last-mile recoverability.

Mitigation: acting under time, trust, and human limits

Mitigation is where prediction becomes expensive. Quantum-oriented papers in the corpus locate mitigation in combinatorial re-optimization: vehicle and load configuration, disruption rerouting, and unit-load-device packing under broken capacity [5], [19], [21]. These remain mostly prospective. Classical digital twins can already host what-if mitigation without quantum hardware [1]. IoT–AI–quantum convergence is best read as a layered option: sense with IoT, predict with AI, and reserve quantum devices for the hardest packing and scheduling islands [14].

Trust and governance constrain which mitigations are allowed to execute. AI–blockchain integration is argued to make multi-party mitigation auditable who rerouted what, on the basis of which sensor claim [3]. Industry 5.0 work insists that automation remain human-centric: the operator is not a residual error term but the locus of exception handling and ethical override [15]. Early swipe-controller work is a primitive instance of that locus an operator gesture that changes machine state [4]. In a modern control tower the gesture is a dashboard confirmation; the design problem is the same: latency, error, and authority.

Exponential modulation properties of the FKF transform are proposed for secure digital supply-chain networks [13]. If spectral features can be modulated, they can in principle carry integrity marks, which matters when mitigation actions are triggered by signals that an adversary might spoof.

Monitoring: residual learning after the action

Monitoring closes the loop. Digital-transformation reviews emphasize continuous visibility and the still-weak state of standardized resilience metrics [23]. Smart-mobility and ITS surveys describe the data exhaust probe vehicles, charging networks, traffic control that can feed post-event models [20]. Green-AI monitoring extends the dashboard from on-time delivery to emissions and circularity [2]. Spectral frameworks, if they work as claimed, would monitor not only KPI breaches but changes in the frequency content of the network [9]. Sequential convergence results [25] are relevant only insofar as they justify treating streaming updates as well-defined objects in the transform's test-function space. A time displacement of the operational signal,

$$x_e(t - \tau_e),$$

produces a corresponding phase modification in its Fourier component. The FKF representation therefore provides a mechanism for separating an actual change in system dynamics from a simple temporal displacement [8], [12]:

$$\mathcal{F}_{FKF}\{x_e(t - \tau_e)\} = e^{-i\omega\tau_e} X_e(\omega, \lambda).$$

Here, denotes the delay associated with echelon . The scale component remains structurally separated from the temporal phase factor, making the representation useful for identifying delayed information, replenishment propagation, transportation latency, and synchronization differences among supply-chain stages [18], [22].

Exponential modulation provides another important spectral operation [13]. For a modulated signal of the form $e^{at}x_e(t)$, the corresponding spectral behavior can be represented schematically as a translation in the complex frequency domain:

$$\mathcal{F}_{FKF}\{e^{at}x_e(t)\} = X_e(\omega, +ia\lambda)$$

and scale-dependent signatures. Across a multi-echelon network, supplier, distribution-center, warehouse, and last-mile signals may occupy different regions of the joint (ω, λ)spectral domain even when their time-domain trajectories appear relatively similar [7], [8], [9], [11].

IV. CONCEPTUAL FRAMEWORK: PREDICT–MITIGATE

Sequential The framework is a loop, not a stack. Four layers sit under the loop; the loop itself has two half-cycles.

Enabling layers

- Physical and energy layer. Fleets, warehouses, batteries, charging, and solar-hybrid architectures determine feasible recovery [6], [16], [18], [22]. Theft and integrity of physical plant remain first-order risks [17].
- Sensing and interface layer. IoT and ITS streams [14], [20], operator interfaces [4], and human-centric Industry 5.0 controls [15] decide what the model is allowed to see and what a person is allowed to override.
- Intelligence layer. Learning models, digital twins [1], spectral FKF/FKL machinery [7], [8], [9], [10], [11], [12], [13], [24], [25], and quantum annealing for selected combinatorial islands [5], [19], [21].
- Trust and sustainability layer. Blockchain provenance [3], green-performance objectives [2], and the digital-resilience capabilities catalogued in [23].

The prediction half-cycle

Raw multi-echelon series, text, and sensor packets are transformed into features. Spectral methods contribute shift-invariant and distributional features [7], [8], [10], [12], [24], [25]; learning models contribute calibrated probabilities [2], [14], [23]; twins contribute simulated futures [1]. The output is not a single risk score. It is a bundle: event probability, expected duration, cascade depth, energy-feasibility flag, and data-integrity flag.

The mitigation half-cycle

The bundle is passed to a planner that may be a rule, a mixed-integer programme, a twin search, or—where the instance is small and highly combinatorial—a quantum annealer [19]. Candidate actions are filtered by blockchain-auditable policy and by a human operator under an Industry 5.0 protocol [3], [15]. Executed actions change the physical layer; residuals return to the spectral and learning models. Exponential modulation [13] is an optional integrity wrapper on the residual channel.

Design principles

Three principles follow. First, prediction without a feasible energy and capacity envelope is decorative [6], [16], [18], [20], [22]. Second, mitigation without a trust and override channel is unsafe [3], [4], [13], [15]. Third, multi-scale spectral structure and ordinary machine learning are complements: the former is a candidate feature factory for the latter, not a replacement for it. The digital-transformation SLR's warning about inconsistent metrics [23] applies directly: the loop is only as good as the metrics used to close it [9], [23].

Findings

Four findings survive a conservative reading of the corpus.

Finding 1. AI for SCRM is not one method. It is a division of labour among detectors (learning and spectral), evaluators (twins and differential transforms), and actors (optimizers, annealers, and humans). Reviews that flatten all of this into "machine learning for risk" lose the mitigation half of the problem [23], [14].

Finding 2. Data integrity is part of prediction. Blockchain [3], modulated spectral marks [13], and infrastructure integrity sensing [17] are not adjacent curiosities; they determine whether an early-warning score is usable.

Finding 3. Physical energy state is part of mitigation feasibility. Electrified and solar-hybrid fleets change the meaning of a "backup carrier" [6], [16], [18], [20],

[22]. Models trained on diesel-era recoveries will mis-rank options.

Finding 4. Maturity is uneven. Digital twins, AI analytics, and Industry 5.0 governance are nearer to managerial use [1], [15], [23]. Quantum annealing and the FKF/FKL family are, on the evidence in this corpus, still methodological programmes. They should be treated as research options, not as deployed controls.

Intelligent Supply Chains

For an asset a, let its digital-twin state be represented by

$$\mathbf{z}_a^{DT}(t) = [p_a,(t), I_a,(t), q_a,(t), c_a(t)E_a(t)m_a(t)\mu_a(t)],$$

where the state may include physical location p_a, inventory I_a, quality q_a, custody c_a, energy E_a, maintenance condition m_a, and associated transaction or provenance metadata μ_a. The corresponding physical state can be represented by $\mathbf{z}_a^P(t)$. A generic synchronization error is then defined as

$$\varepsilon_{DT}(t) = \|\mathbf{z}_a^P(t) - \mathbf{z}_a^{DT}(t)\|.$$

When exceeds an application-specific tolerance, the digital twin can initiate state re-estimation, sensor verification, or model updating. This mechanism is particularly important when digital and physical states drift under disruption [1], [3], [14].

mathematical signal analysis with practical operational intelligence

FKF-derived spectral features and digital-twin indicators can be incorporated into these coefficients as time-dependent weights or operational constraints. For example, a resonance indicator may increase the penalty associated with a disrupted transportation lane, a detected lead-time shift may modify the cost of a transit connection, and an energy-scale excursion may restrict the selection of a particular vehicle class. In this manner, spectral intelligence can influence the optimization problem without requiring the quantum layer to reproduce the underlying signal-processing operations [1], [7], [8], [10], [19], [21].

V. LIMITATIONS

The reconstruction is bounded by its closed corpus. It cannot claim completeness relative to the AI-SCRM field, which contains large SLRs on interconnectivity, explainability, and prescriptive analytics that are outside [23]. Several cited items are short journal or contest pieces rather than multi-study evidence [5], [16], [19]. Spectral and quantum claims are not independently replicated here. Adjacent 2014 control and anti-theft papers are historically and thematically distant from contemporary AI risk prediction; their inclusion is an artefact of the reconstruction request and is labelled as such [4], [17].

VI. CONCLUSION

Artificial intelligence improves supply-chain risk work when it is coupled to a sensing layer, a trust layer, a human layer, and a physical energy layer. The twenty-five works assembled for this reconstruction supply pieces of all four layers, with very different levels of maturity. Digital twins, AI–blockchain provenance, Industry 5.0 governance, and digital-resilience reviews form the usable core. Convergent IoT–AI–quantum architectures and quantum annealing describe a plausible next computational tier. The FKF/FKL programme offers a distinctive, still-unproven feature calculus for multi-echelon dynamics. Energy-mobility and infrastructure-security papers define constraints and sensing analogs that any serious risk model must eventually ingest. The PREDICT–MITIGATE loop is the simplest architecture that keeps those pieces from collapsing into a technology list. The research agenda is to test that architecture on shared data, with shared metrics, rather than to enlarge the list.

and frequency-domain methods.

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