Toward Intelligent Supply-Chain Resilience: An AI-Driven Framework for Risk Prediction and Mitigation

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Abstract—

The increasing complexity and interdependence of global supply networks require more proactive approaches to disruption prediction and resilience management. This paper proposes a conceptual AI-enabled PREDICT–MITIGATE framework integrating machine learning, IoT sensing, digital twins, blockchain traceability, intelligent transportation, FKF/FKL spectral methods, green logistics, and quantum logistics optimization. The framework establishes a closed-loop architecture that converts multi-source supply-chain observations into predictive risk profiles and subsequently supports constraint-aware mitigation and continuous feedback. Artificial intelligence enables disruption forecasting and decision support; FKF/FKL spectral methods contribute temporal and multi-scale features; digital twins enable counterfactual scenario evaluation; blockchain records provenance for trusted traceability; green-logistics objectives constrain environmentally feasible recovery; and quantum optimization provides an emerging option for computationally intensive logistics problems. Cybersecurity, energy availability, and human oversight are incorporated to improve practical feasibility. The study identifies the complementary roles and different maturity levels of these technologies and highlights future requirements for explainable AI, multi-tier visibility, interoperable digital twins, autonomous mitigation, and responsible governance. The proposed framework offers a pathway toward intelligent, adaptive, and continuously learning supply-chain resilience.

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

The increasing interdependence of global supply networks has transformed supply-chain resilience into a critical requirement for modern enterprises. Digital transformation, interconnected logistics, intelligent transportation, and emerging computational technologies are reshaping how organizations identify, assess, and respond to disruptions. Digital twins provide a dynamic representation of supply-chain operations and support resilient, adaptive decision-making [1], [26], [27], [39]. Artificial intelligence has become a principal enabler of predictive analytics, sustainable logistics, and intelligent supply-chain management [2], [28], [32]. Machine-learning models can forecast disruption probability, but their operational value depends on interpretability as well as predictive performance [29], [30]. The integration of AI with blockchain further strengthens transparency, traceability, data integrity, and resilience across distributed supply networks [3], [31].

Digital twins maintain a living replica of physical supply-chain assets, inventories, lead times, and transport lanes. Combined with real-time IoT observations, they allow planners to evaluate alternative disruption scenarios before an action is executed in the physical network [1], [26], [27]. This counterfactual capability is essential for ripple-effect analysis, in which a local delay or capacity loss propagates across echelons [38], [39]. In parallel, Industry 5.0 promotes human-centric automation in which autonomous technologies complement rather than replace managerial judgment [15]. Intelligent transportation systems and smart mobility technologies improve the visibility and adaptability of logistics operations by integrating connected vehicles, sensing, communication, and data-driven optimization [20].

Green logistics must enter risk models as an operating constraint rather than a reporting afterthought. AI-based approaches support demand prediction, route optimization, resource allocation, and energy-efficient transportation [2]. Electrified fleets add a further coupling between logistics risk and energy availability: battery chemistry and management systems [6], plug-in hybrid battery sizing [18], solar-assisted electric mobility [22], and hybrid vehicle architectures [16] determine whether a predicted reroute is physically feasible after a grid or charging disruption. Ignoring these constraints causes recovery plans to overstate last-mile capacity.

Existing studies often treat these technologies independently, leaving a gap in an integrated architecture for AI-driven risk prediction and mitigation. The relationship among predictive intelligence, digital-twin simulation, blockchain traceability, FKF/FKL spectral disruption analysis, green-logistics objectives, and quantum logistics optimization remains insufficiently consolidated [23], [28], [32]. This study therefore develops the PREDICT–MITIGATE framework, which converts multi-source observations into a multidimensional risk profile and then into constraint-aware interventions. The aim is earlier disruption detection, adaptive decision-making, energy-aware resilience assessment, trusted data exchange, and sustainable recovery, together with a testable research agenda.Supply-chain disruptions may originate from supplier failures, transportation delays, cyberattacks, geopolitical instability, extreme weather, energy constraints, or sudden demand variations. Conventional risk-management approaches generally depend on historical information, predefined scenarios, and delayed human intervention, which limits their ability to respond to rapidly evolving conditions [23], [28]. AI-based machine learning and deep-learning techniques can process heterogeneous information from enterprise systems, supplier databases, logistics platforms, IoT sensors, weather services, and external risk indicators to identify anomalies and predict potential disruptions [2], [29], [32]. Explainable formulations are required when a predicted score triggers costly mitigation [30]. The convergence of IoT sensing, AI analytics, and quantum computing supplies an additional foundation for smart logistics ecosystems capable of continuous monitoring and computationally intensive decision support [14], [21].

II. CONCEPTUAL AND TECHNOLOGICAL BACKGROUND

Disruption exposure, adaptive resilience, and predictive risk management

A supply-chain risk arises when material, information, or financial flows depart from their expected behavior in ways that threaten operational continuity, service performance, or economic outcomes. Supply-chain resilience describes the capacity of a network to anticipate and withstand disturbances, restore disrupted functions, and adapt to subsequent changes [23], [38]. Predictive risk management estimates when a disruption may emerge, how severe it may become, how long it may persist, and how it could propagate through interconnected tiers [28], [32]. Mitigation then includes alternative sourcing, inventory redistribution, transportation-mode changes, contractual adjustments, cybersecurity response, green rerouting, and automated operational reconfiguration evaluated inside a digital twin before physical execution [1], [26].

Research on digital transformation has identified connectivity, visibility, analytics, and automation as major capabilities for resilient supply-chain systems [23]. Rather than treating these capabilities only as tools for reconstructing past events, this study uses them to create a forward-looking prediction–mitigation loop. Artificial intelligence supplies calibrated forecasts [2], [29]; digital twins convert those forecasts into network-level consequences [1], [26], [39]; blockchain traceability authenticates the observations on which both layers depend [3], [31]; and FKF/FKL spectral methods extract multi-scale structure from lead-time and flow signals that standard time-domain detectors may miss [7], [9], [11].

Research boundary and corpus-based reconstruction

Large-scale systematic reviews of artificial intelligence for supply-chain risk management commonly use bibliographic databases such as Scopus and Web of Science to classify algorithms, applications, and stages of risk management [28], [32]. The present study does not duplicate those field-wide reviews. Instead, it reconstructs an integrated architecture from a defined corpus that connects digital twins [1], green logistics and AI [2], blockchain traceability [3], [31], FKF/FKL spectral analysis [7]–[13], [24], [25], quantum logistics [5], [19], [21], Industry 5.0 control [15], and digital-transformation evidence on resilience measurement [23]. Complementary reviews on explainable AI [30] and machine-learning risk prediction [29] locate the intelligence layer within the broader SCRM literature.

Interconnected research themes

Six principal themes emerge from the selected references.

Resilient digital supply networks: Digital-twin technology supports dynamic representation, ripple-effect analysis, and adaptive management of global supply chains [1]. AI–blockchain integration improves transparency, traceability, and trusted information exchange across partners who do not share a common enterprise system [3], [31]. Digital-transformation research provides the broader resilience context and documents the continuing absence of standardized resilience metrics [23].

AI for sustainable operations and green logistics: AI applications in sustainable logistics provide the intelligence layer for demand prediction, routing, and resource allocation under environmental constraints [2]. Related work on digital twins in sustainable material processing shows how simulation and learning can be coupled for resource-efficient operations [36]. Industry 5.0 extends this perspective by placing human operators at the center of exception handling rather than treating automation as a complete substitute for judgment [15].

IoT, AI, and quantum logistics: IoT sensing, AI analytics, and quantum computation form a layered architecture for intelligent logistics ecosystems [14]. Quantum approaches have been examined for supply-chain optimization [5], transportation and logistics [21], and disruption-aware unit-load-device configuration [19]. In the proposed framework, quantum annealing is reserved for combinatorial packing, slotting, and routing instances that remain hard for classical heuristics after disruption, while AI retains responsibility for prediction and digital twins retain responsibility for scenario evaluation.

FKF/FKL spectral intelligence: The mathematical strand includes FKF and FKL transform formulations, distributional extensions, sequential convergence, time-shift analysis, exponential modulation, and spectral characterization of multi-echelon supply-chain dynamics [7]–[13], [24], [25]. These methods treat lead-time and flow series as signals in which disruptions appear as resonances, scale-dependent energy shifts, or delay-induced phase changes rather than as isolated binary events. The resulting spectral features can be passed to machine-learning classifiers without replacing those classifiers.

Electrified mobility and energy dependencies: Battery technologies and management systems [6], plug-in-hybrid battery sizing [18], solar-assisted mobility architectures [16], [22], and intelligent transportation systems [20] define physical and energy constraints that must enter AI-based risk models. A digitally predicted recovery path is operational only if charging queues, state of charge, and on-board generation can support the assigned fleet movement.

Operational control and infrastructure security: Human–machine interfaces [4] and power-line-carrier integrity monitoring [17] are not conventional SCRM methods, but they specify two design requirements that the framework inherits: authorized human override at the control tower and protection of the sensing infrastructure on which prediction depends.

III. AI-ENABLED SUPPLY-CHAIN RISK MANAGEMENT: STAGE-WISE SYNTHESIS

Early-Warning Generation: From Data Streams to Risk Signatures Risk identification begins by transforming heterogeneous telemetry, documents, and operational observations into recognizable risk signatures. IoT platforms and intelligent transportation systems provide continuous data streams on location, dwell time, temperature, traffic, and charging state [14], [20]. Blockchain traceability anchors those observations to an auditable provenance record so that later predictions are not computed on unverifiable or altered inputs [3], [31]. Infrastructure-integrity monitoring remains necessary because a compromised sensor or communication link can inject false early-warning signals [17].

The spectral strand offers a complementary reading of the same streams. Supply-chain disruptions can appear as resonances, time shifts, and multi-scale energy changes rather than as isolated events. Multi-scale spectral analysis and residue-based resonance extraction detect hidden periodic stress in hybrid-vehicle and logistics systems [7]. Shift-invariant FKF analysis of multi-echelon lead times preserves relevant spectral structure when a disruption inserts delay without rewriting the underlying pattern [8], [12]. The FKF resilience framework treats transform outputs as persistent monitoring signatures [9], while the FKL transform supplies an alternative representation for related classes of supply-chain signals [11]. Distributional extensions and sequential-convergence results support application to irregular and heavy-tailed disruption data [24], [25].

These FKF/FKL signatures are not used as stand-alone alarms. They are encoded as features for AI detectors that also consume enterprise, supplier, and textual risk indicators [2]. Comparative evaluation against Fourier, wavelet, and learned embeddings remains an open experimental requirement and is stated as such in the research agenda.

Green logistics introduces an additional identification dimension. Environmental and regulatory risks remain poorly represented when prediction systems optimize only cost and service [2]. Effective identification therefore depends not only on the detection algorithm but also on the loss function used to define organizational risk. Emissions intensity, energy availability, and circularity indicators should enter the same early-warning layer that monitors stockouts and delays.

Risk Quantification: Linking Predictions with Network Consequences

Risk assessment extends detection by estimating probability, severity, exposure, and propagation. Digital twins are the natural instrument for this step because they permit alternative disruption scenarios to be simulated without exposing the physical network to failure [1]. Ripple-effect analytics connect a local shock to cascade depth, recovery time, and service loss across tiers [38]. Digital-transformation reviews associate predictive analytics with improved responsiveness while noting the continuing lack of consistent resilience measurements [23].

Spectral differential properties of the distributional FKF transform provide a second assessment view: they ask how a perturbation in the lead-time distribution changes the resilience signature, not merely whether a resonance exists [10], [24]. Energy and mobility research supplies the physical envelope for the same assessment. Battery chemistry, management systems, and sizing determine residual transport capacity after grid or charging disruptions [6], [18]. Solar-assisted and hybrid architectures add on-board generation and therefore enlarge or shrink the feasible recovery set [16], [22]. An AI model that ignores this envelope will overestimate last-mile recovery.

Intelligent Intervention: From Prediction to Adaptive Action

Mitigation converts a risk profile into an operational intervention. Candidate actions include alternative sourcing, inventory repositioning, mode switching, green rerouting, and unit-load-device reconfiguration. Digital twins already support counterfactual search over these options [1], [26]. Quantum logistics studies frame the hardest remaining tasks as combinatorial optimization over transportation configuration, gate slots, routing, and disrupted unit-load-device packing [5], [19], [21]. The resulting architecture is layered rather than monolithic: IoT senses, AI predicts, the digital twin evaluates network consequences, and quantum annealing is applied only when the instance is small enough and combinatorial enough for annealing to be a credible solver [14].

Trust and authority decide whether a recommended action is executed. Blockchain traceability can record the data, model version, predicted profile, and authorized decision in an auditable chain [3], [31]. Industry 5.0 places the human operator at the center of exception handling, supervision, and ethical intervention [15]. Control-tower interfaces must therefore expose override rights, latency budgets, and confirmation states [4]. Exponential-modulation properties of the FKF transform have been proposed as an integrity mechanism for spectral monitoring channels in digital supply networks [13], which becomes relevant when mitigation depends on signals that could be spoofed.

Feedback Intelligence: Continuous Monitoring and Model Updating

The final stage evaluates implemented interventions and updates subsequent predictions. Continuous visibility is necessary, yet standardized resilience metrics remain weak across digital-transformation studies [23]. Smart mobility systems generate post-event traces from connected vehicles, charging infrastructure, and traffic management that can retrain both spectral monitors and learning models [20]. Green-logistics monitoring extends the feedback set beyond delivery and cost to emissions, energy consumption, and circularity [2], [36]. Residual observations return to the PREDICT phase so that the loop remains closed.

The framework is therefore a closed operational loop rather than a technology stack. Four enabling layers support the loop, and its operating logic consists of two complementary phases: prediction and mitigation. Figure 1 presents the layered foundation; Figure 2 presents the operating cycle.

IV. INTEGRATED PREDICTIVE–ADAPTIVE SUPPLY-CHAIN ARCHITECTURE

The PREDICT–MITIGATE architecture converts multi-source observations into a risk profile and then into a feasible, auditable intervention. Four layers define what the loop is allowed to see and to change; the two phases define how information moves.

Figure 1. Four enabling layers of the PREDICT–MITIGATE architecture.

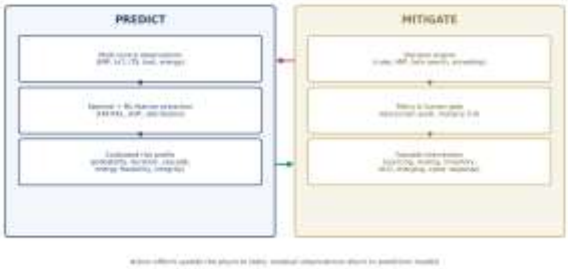

Figure 2. Closed-loop PREDICT–MITIGATE operating cycle.

Foundational Architecture and Enabling Capabilities

- Physical, mobility, and energy foundation: Fleets, warehouses, batteries, charging infrastructure, and solar-hybrid vehicle architectures define the feasible recovery envelope [6], [16], [18], [22]. Physical-asset theft, tampering, and infrastructure integrity remain operational risks that the sensing layer must detect [17].
- Sensing, connectivity, and human-interaction layer: IoT and intelligent transportation streams [14], [20], operator interfaces [4], and Industry 5.0 controls [15] determine both the information available to models and the extent of authorized human intervention.
- Analytics and computational intelligence layer: This layer combines machine-learning models for calibrated prediction [2], digital twins for counterfactual network search [1], FKF/FKL spectral techniques for multi-scale and shift-invariant features [7]–[13] and quantum annealing for selected combinatorial logistics problems [5], [19], [21].
- Trust, governance, and sustainability layer: Blockchain provenance and accountability [3], [31], green-logistics objectives [2], explainability requirements [30], and digital-resilience capabilities [23] establish the conditions under which a prediction may be trusted and an action may be executed.

Predictive Intelligence Cycle

The prediction phase begins with multi-echelon time series, textual information, energy-state readings, and sensor observations. FKF/FKL methods generate shift-invariant and distribution-sensitive features [8], [10], [12], [24]. Machine-learning models estimate calibrated probabilities of disruption class, duration, and cascade depth [2]. Digital twins generate simulated future states under alternative shocks [1]. Blockchain checks data integrity before a score is accepted [3]. The output is not a single risk index. It is a multidimensional profile containing event probability, expected duration, cascade depth, energy-feasibility status, green-constraint status, and data-integrity status. That profile is the contract between prediction and mitigation. Every subsequent optimizer, twin search, or human review operates on the same structured object rather than on an opaque score.

The risk profile is transferred to a decision engine that may employ predefined policies, mixed-integer optimization, digital-twin search, or quantum annealing when the residual problem is sufficiently small and combinatorial [5], [19], [21]. Green-logistics costs and charging constraints are included in the feasible set so that a mathematically cheaper route is rejected when it violates emissions or energy limits [2], [6], [22].

Candidate interventions are evaluated against blockchain-auditable policies and Industry 5.0 human-oversight requirements [3], [15], [31]. Once an action is executed, its consequences modify the physical operating state, while residual observations return to the spectral and learning models. Exponential modulation [13] may encode integrity marks on the residual-information channel so that feedback used for the next prediction cannot be silently altered.

Core Architectural Principles

Three principles characterize the architecture. First, predictive intelligence must operate inside a physically and energetically feasible capacity envelope [6], [18], [22]; otherwise a forecast has little operational value. Second, automated mitigation requires trusted information, blockchain-traceable authority, and an explicit human override [3], [4], [15]. Third, FKF/FKL spectral analysis and conventional machine learning are complementary: spectral representations are feature generators for learning models rather than competing predictors [7], [9], [11]. Inconsistent resilience measurement [23] further implies that claims about loop performance cannot be compared until metrics stabilize.

V. FUTURE RESEARCH AGENDA

The agenda is written as questions that a subsequent systematic review or empirical study can test. Figure 3 groups the questions into nine complementary workstreams.

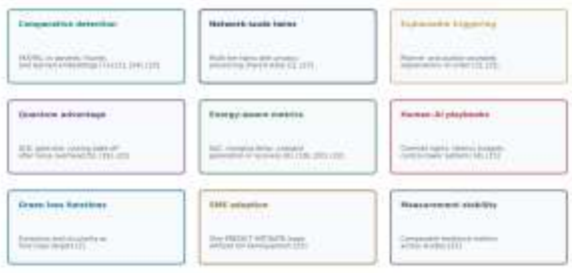

Figure 3. Testable questions in the future research agenda.

Comparative detection. Do FKF/FKL features improve disruption classifiers over standard wavelet, Fourier, and learned embeddings on public multi-echelon datasets [7]–[12], [24], [25], [29]? Without that comparison, the spectral strand remains self-contained.

Network-scale twins. Move digital twins from plant or lane replicas to multi-tier networks with shared but privacy-preserving state, so that ripple-effect simulation is no longer confined to a single firm [1], [23], [39].

Explainable triggering. When an AI or spectral score launches a costly mitigation, what explanation is accepted by planners and by auditors reading a blockchain record [3], [15], [31]?

Quantum advantage under disruption. Identify unit-load-device, gate-slot, and routing instances where annealing outperforms strong classical heuristics after noise and embedding overhead [5], [19], [21].

Energy-aware resilience metrics. Include state of charge, charging-queue delay, and on-board generation in recovery-time metrics for logistics networks [6], [18], [20], [22].

Human–AI playbooks. Specify Industry 5.0 override rights, latency budgets, and interface patterns so that control-tower staff can reject a model action in seconds [4], [15].

Green objectives inside the loss. Treat emissions, energy use, and circularity as first-class prediction and optimization targets rather than report-only add-ons [2].

SME adoption. Cost, skills, and interoperability remain barriers to digital resilience programs [23]. Slim versions of the PREDICT–MITIGATE loop are needed that do not assume a full multi-tier twin or access to a quantum queue.

Measurement. Until resilience metrics stabilize, claims of large forecasting or response-time gains that appear in digital-SCR reviews cannot be compared across papers [23].

The same agenda has implications for researchers, practitioners, and scholarly communication. Figure 4 summarizes those pathways.

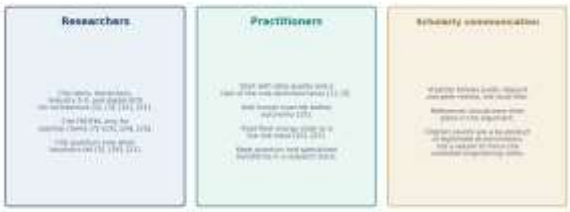

Figure 4. Implication pathways for researchers, practitioners, and scholarly communication.

For researchers

Treat the technologies as complementary instruments with unequal maturity. Cite digital-twin and ripple-effect research when the claim concerns scenario evaluation or cascade dynamics [1]. Cite AI and explainable-prediction research when the claim concerns detection or scoring [2]. Cite blockchain studies when the claim concerns provenance and audit [3], [31]. Cite the FKF/FKL series when the contribution is spectral feature construction [7]–[13], [24], [25]. Cite quantum logistics papers only for combinatorial packing, slotting, or routing instances [5], [19], [21]. Cite battery, mobility, and interface papers only for the constraint or control surface they specify [4], [6], [16], [17], [18], [20], [22].

For practitioners

Build the loop from the middle outward. Start with identification data quality, blockchain-traceable event records, and a digital twin of the two or three lanes that dominate disruption cost [1], [3]. Embed green-logistics and fleet energy state as live inputs [2], [20], [22]. Add human override before adding autonomy [15]. Keep FKF/FKL feature extraction and quantum solvers on a research track until a controlled comparison against standard detectors and classical heuristics is available.

For indexing and scholarly communication

Scholarly communication should keep methods aligned with claims. Digital twins, green logistics, blockchain traceability, FKF/FKL analysis, quantum logistics, and artificial intelligence should be cited where they do work in the argument, not as an undifferentiated technology list. Preprint or peer-reviewed deposit creates a public record; citation then follows from use.

VII. RESEARCH AGENDA FOR NEXT-GENERATION INTELLIGENT SUPPLY CHAINS

Beyond the nine testable questions, six longer-term directions follow for next-generation intelligent supply chains. Figure 5 maps those directions.

Figure 5. Research directions for next-generation intelligent supply chains.

Transparent and Explainable Risk Intelligence

Future models must explain predicted disruptions, risk classifications, and recommended interventions so that planners can assess reliability and satisfy emerging accountability requirements [3], [15], [30]. FKF/FKL signatures should be translated into operational language delay resonance, heavy-tailed lead-time shift, or multi-scale energy change rather than remaining opaque transform outputs [9], [10].

Network-Level Risk Intelligence

Visibility should expand from first-tier relationships to multi-tier networks. Models can combine supplier, logistics, financial, geopolitical, energy, and operational information to estimate cascade depth [1], [14], [23]. Multi-echelon lead-time representations remain a natural testbed because FKF time-shift properties are defined on precisely those series [8], [12].

Climate and Sustainability Integration

Climate exposure, resource constraints, emissions, energy availability, and environmental regulation should enter both the prediction loss and the mitigation feasible set [2], [6], [16], [22]. Green logistics is then part of resilience design rather than a parallel reporting stream.

Cross-Organizational Digital Twins

Interoperable digital twins are required if scenario evaluation is to cross organizational boundaries. Future architectures must exchange operational state while respecting differences in data structures, platforms, ownership, privacy, and governance [1], [3], [23]. Blockchain traceability and integrity-preserving encodings of shared monitoring channels are candidate mechanisms for that exchange [13], [17], [31].

Autonomous and Agent-Based Mitigation

Agentic AI systems that select and execute mitigation strategies are an emerging frontier [14], [15], [32]. Research must determine when autonomous intervention is appropriate, how cost, service, and green objectives are resolved, and how agents remain inside predefined authority bounds. Disrupted unit-load-device configuration and routing remain candidate domains for selective quantum assistance [5], [19], [21].

Responsible AI and Human-Centered Resilience

Ethical governance, cybersecurity, human–AI collaboration, and operational oversight remain first-order design problems [3], [4], [15], [30]. Intelligent supply chains should therefore pursue not only higher autonomy and accuracy but also accountable decision-making and meaningful human control. Streaming spectral monitors should be updated under mathematically consistent sequential conditions [24], [25] so that continuous learning does not silently invalidate earlier resilience signatures [9].

VIII. CONCLUSION

This study developed an integrated perspective on AI-driven supply-chain risk prediction and mitigation by connecting artificial intelligence, digital twins, IoT sensing, blockchain traceability, green logistics, intelligent transportation, quantum logistics optimization, and FKF/FKL spectral analysis. The PREDICT–MITIGATE framework treats resilience as a closed loop: multi-source observations become spectral and learned risk signatures; digital twins convert those signatures into network consequences; a constrained decision engine proposes mitigation; blockchain and human oversight authorize execution; and residual evidence updates the next prediction. Prediction is required to respect physical, energy, capacity, data-integrity, and cybersecurity constraints. AI supplies predictive intelligence, FKF/FKL methods contribute multi-scale and temporal features, digital twins support scenario analysis, quantum optimization addresses selected combinatorial logistics tasks, and blockchain together with Industry 5.0 governance keep intervention auditable. Quantum and spectral components remain emerging and require comparative validation; their combination with established learning and simulation methods nevertheless defines a coherent path toward secure, explainable, sustainable, and adaptive supply chains.

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