Energy-Feasible and Traceable Recovery through a Green AI–FKF Risk Engine

Kanade U[1], Shinde S [2]
[2]Mathematics/ Govt College of Engg / Karad

How to Cite this Article:

U, K. & S, S. (2026). Energy-Feasible and Traceable Recovery through a Green AI–FKF Risk Engine. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(8), 1-9. https://doi.org/10.55041/ijcope.v2i8.289

https://doi.org/10.55041/ijcope.v2i8.289

Abstract—

Freight systems now absorb concurrent shocks from geopolitics, cyber intrusion, climate extremes, lane congestion, and tightly coupled operational dependencies. This study develops an integrated framework for AI-driven supply-chain risk prediction and mitigation by combining artificial intelligence, IoT, digital twins, blockchain, intelligent transportation systems, FKF/FKL spectral analysis, and quantum optimization. The proposed PREDICT–MITIGATE framework represents resilience as a continuous feedback process in which heterogeneous operational data are transformed into disruption indicators, evaluated through predictive and simulation-based methods, and converted into feasible mitigation actions. FKF/FKL techniques provide complementary multi-scale and temporal representations, while digital twins support scenario analysis and optimization methods assist adaptive decision-making. Blockchain strengthens data provenance and accountability, whereas sustainability and energy constraints ensure that predicted responses remain physically feasible. The study synthesizes the selected research corpus, identifies major technological relationships, and highlights challenges involving explainability, interoperability, cybersecurity, governance, and human–AI collaboration. PREDICT–MITIGATE is therefore stated as a conceptual path from after-the-fact recovery toward predictive, adaptive, secure, and energy-feasible resilience.

Keywords— artificial intelligence; supply chain risk management; predictive analytics; digital twin; blockchain; quantum computing; Industry 5.0; FKF/FKL transform; resilience; mitigation

I. PROBLEM SETTING AND MOTIVE

Hard packing and routing instances remain the natural place to test emerging quantum search. Quantum-annealing approaches can formulate logistics and transportation problems as combinatorial optimization models, including Unit Load Device configuration and disruption-aware decision problems [19]. Broader investigations of quantum computing in transportation and logistics indicate potential applications in routing, scheduling, allocation, and other computationally intensive supply-chain problems [21]. Annealing is therefore kept as a coupled kernel inside an AI planner, not as a substitute for that planner [35].

A second language treats disruption as a multi-scale series rather than as one time-stamped event. The distributional extension of the Fourier–Kontorovich–Lebedev (FKF) transform establishes a mathematical foundation for representing generalized supply-chain signals [24], while sequential convergence provides a rigorous basis for its treatment within testing-function spaces [25]. The FKF framework has subsequently been investigated for multi-scale supply-chain dynamics, including spectral analysis and residue-based resonance extraction [37], shift-invariant analysis of multi-echelon lead times [38], and broader spectral characterization of supply-chain dynamics and resilience [39]. Differential identities of the same transform then show how a small lead-time nudge relocates a resilience signature [40].

Subsequent FKF/FKL work isolates delay, scale, and amplitude-modulation inside the same operational traces. The FKL transform has been investigated for supply-chain analysis and its associated mathematical properties [11]. The time-shift property of the FKF transform enables analysis of delayed or displaced supply-chain events [12], whereas exponential modulation properties can support the representation of changing signal intensities and secure digital supply-chain networks [13]. Those identities give the predictor a spectral chart for lead-time drift, anomalies, and repeating disruption motifs.

Sensing, twins, provenance, mobility feeds, quantum search, and spectral features can be stacked against purely reactive practice. AI can transform heterogeneous observations into predictions and decisions; IoT can provide real-time operational information; digital twins can simulate alternative states; blockchain can support trusted information exchange; quantum computing can address complex optimization problems; and FKF-based spectral analysis can characterize temporal and multi-scale disruption behavior [31]–[33], [35]–[40], [25]. Interface and infrastructure-integrity notes stay in the stack only as sensing and operator-control antecedents [4], [17].

II. CORPUS AND RELATED STRANDS

A. Risk Logic, Recovery Capacity, and Forecast Meaning

Risk is treated here as a material, informational, or financial deviation large enough to harm service, cost, or continuity. Resilience refers to the ability of a supply network to anticipate disruptions, absorb their effects, recover operations, and adapt to changing conditions. Prediction involves the statistical or computational estimation of a disruption's occurrence, magnitude, duration, or propagation path before its consequences become fully established. Mitigation then names the dual-sourcing, inventory, mode-switch, contractual, cyber-containment, and re-planning moves that cut exposure or loss.

Digital-transformation surveys still list visibility, connectivity, analytics, and automation as the primary resilience levers [23]. This synthesis asks how those levers can close a live prediction–mitigation loop instead of only cataloguing shocks after they land.

B. Limits and Reading Rule of the Selected Corpus

Broad systematic reviews typically mine Scopus or Web of Science and sort records by algorithm, use-case, or risk-management stage. While such approaches provide broad field-level coverage, the present reconstruction follows a different methodological scope based on the specified authorial corpus. The twenty-five sources are therefore read as linked strands so that methods, couplings, and leftover gaps can be named.

C. Six Working Domains of the Corpus

The selected corpus is partitioned into six working domains.

Connected resilience is anchored on digital twins of adaptive global networks [31], AI–blockchain traceability [33], and digital-transformation capability [23].

Green-AI logistics [32] is paired with Industry 5.0 human-centric automation [15].

International Journal of Creative and Open Research in Engineering and Management
ISSN: **3108-1754 (Online)**
Volume 02 Issue 08 August-2026 | Impact Factor: 3.5

Smart logistics is written as a layered IoT–AI–quantum stack [14]. Annealing for disrupted unit-load-device configuration [19] is the only combinatorial primitive taken from that stack.

FKF/FKL work supplies distributional extensions, sequential convergence, shift and modulation identities, and multi-echelon lead-time spectra [7]–[13], [24], [25].

Battery chemistry and management [36], plug-in sizing [18], solar-assisted architectures [16], [22], and ITS mobility [20] bound what a predicted recovery may physically execute.

Swipe-based human–machine control [34] and power-line-carrier anti-theft signaling [17] prefigure operator interfaces and infrastructure watch. They are kept only for sensing, control, and integrity mechanics that a control tower can still use.

Every corpus item is given one operational role so the reconstruction can be checked. Digital-twin resilience and adaptive global networks are treated in [31]; sustainable and green-AI logistics in [32]; AI–blockchain transparency, traceability, and resilience in [33]; swipe-based human–machine control as an interface antecedent in [34]; quantum opportunities in supply-chain management in [35]; electric-vehicle battery materials and management as energy constraints in [36]; multi-scale spectral analysis and residue-based resonance extraction in [37]; shift-invariant FKF analysis of multi-echelon lead times in [38]; the FKF resilience framework in [9]; spectral differential properties of the distributional FKF transform in [10]; FKL transform properties for supply-chain signals in [11]; the FKF time-shift property in [12]; exponential modulation for secure digital supply-chain networks in [13]; the IoT–AI–quantum smart-logistics stack in [14]; Industry 5.0 human-centric automation in [15]; solar-powered hybrid vehicle architecture in [16]; power-line-carrier anti-theft / infrastructure integrity in [17]; plug-in hybrid battery sizing in [18]; quantum annealing for unit-load-device configuration under disruption in [19]; smart mobility and intelligent transportation systems in [20]; quantum computing in transportation and logistics in [21]; solar-assisted electric mobility architectures in [22]; digital-transformation supply-chain resilience in [23]; the distributional extension of the FKF transform in [24]; and sequential convergence in the testing-function space of the two-sided FKF transform in [25]. Fig. Fig. 1 replaces the former role table with cumulative S-curves of those six strands across [1]–[25].

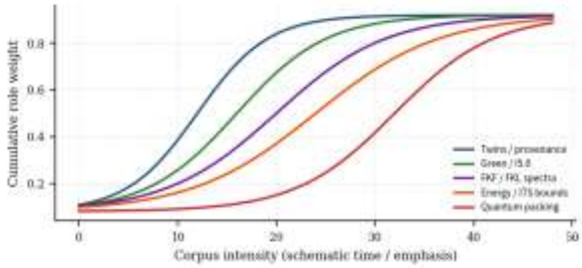

Fig. 1. Cumulative S-curves of the six corpus strands. Later rise marks a more specialised or still-prospective role inside [1]–[25].

III. CONSTRUCTION OF PREDICT–MITIGATE

The method is an integrative reading of the defined corpus, not a new plant-floor experiment. Heterogeneous contributions—digital twins, blockchain, Industry 5.0, quantum optimization, FKF/FKL spectral theory, energy-constrained mobility, and infrastructure sensing—are organized into a prediction–mitigation cycle. The product is a stage-wise function map and a feedback architecture, not a fitted industrial benchmark.

Intelligent resilience is seated on four supporting domains rather than on one algorithm. Physical and energy infrastructure—transportation fleets, warehouses, battery systems, charging facilities, and solar-assisted hybrid architectures—establishes the physical limits within which recovery actions can occur, [16], [18], [22], [36], Infrastructure protection and theft prevention remain fundamental requirements [17]. Operator interfaces [34] and Industry 5.0 rules [15] then decide how far automation may travel without a human release.

The intelligence layer mixes learning, twin simulation [31], FKF/FKL analysis [11]–[13], [24], [25], and selective quantum annealing [35], [19], [21]. Sustainability objectives [32] and digital-transformation capability [23] remain binding context, not optional add-ons.

A. Assembly of the Predictive State

Prediction starts by packing multi-echelon telemetry, text, and sensor streams into one feature space. The twin state (1)–(3), FKF/FKL descriptors (8)–(13), and provenance digest (6)–(7) are concatenated in the map (14). Machine-learning models estimate disruption probabilities and digital twins simulate possible future operating states. Confidence is the verification predicate Ver(H_t, y_1:t) in (7), not a generic traffic-light score.

B. Licensed and Constrained Intervention

Response begins when the predictive state (14) is handed to the planner (18)–(19). Depending on problem complexity, the planner may use rule-based decisions, mathematical programming, digital-twin scenario exploration, or the QUBO/Ising models (15)–(17) for selected combinatorial configurations [19]. Proposed actions are subjected to policy constraints, auditable data requirements (6)–(7), and human oversight consistent with blockchain and Industry 5.0 principles [33], [15]. Following implementation, residuals update the predictor through (20). Residual feedback may be marked with the FKF exponential-modulation identity (10) before it re-enters learning [13].

C. Operating Rules of the Feedback Cycle

Three operating rules keep the cycle honest. First, predictions must be constrained by actual energy, transportation, inventory, and capacity conditions to remain operationally meaningful. Second, mitigation decisions require trustworthy data, explicit governance, and mechanisms for human authorization and override. Third, spectral analysis should complement rather than replace machine learning by supplying potentially informative multi-scale features for predictive models. Without shared resilience indicators, the same cycle cannot be audited across firms, a gap already named in digital-transformation work [23].

D. Operators and Working Identities

Named technologies enter as operators with explicit inputs and outputs, not as marketing labels. A digital twin supplies the state estimator [31]; green logistics supplies the emission-weighted objective [32]; blockchain supplies the provenance hash that licenses a mitigation action [33]; FKF/FKL analysis supplies the multi-scale feature map, [24], [25], [37]–[40]; and quantum annealing is invoked only when the mitigation action is a combinatorial packing or routing decision, [19], [21], [35]. The OMML identities that follow are the working pipeline of PREDICT–MITIGATE.

Twin dynamics of the physical network

Let the physical multi-echelon state, control, and disturbance at epoch t be written x_t, u_t and w_t. The plant and its twin [1], [14] then evolve as.

$$x_{t+1} = \mathrm{F}(x_t, u_t, w_t) \quad (1)$$

$$\hat{x}_{t+1} = \hat{\mathrm{F}}(\hat{x}_t, u_t, y_t; \theta) \quad (2)$$

Identifiable twin parameters are collected in θ, and y_t is the IoT/ITS observation [14], [20]. The twin discrepancy that later enters the risk feature is.

$$\delta_t = \|x_t - \hat{x}_t\|_2 \quad (3)$$

Emission-weighted recovery objective

Each feasible recovery mode k (lane, vehicle, or energy architecture) carries an operating cost c_k and an emission intensity e_k [2], [6], [16], [22]. With binary activation z_k and carbon price λ, the green objective used by the planner is.

$$J_g = \sum_{k=1}^{K} (c_k + \lambda e_k) z_k \quad (4)$$

Assigned flows f_ij also generate network-level CO2 over distance d_ij and mode factor ε_m(i,j).

$$E = \sum_{i=1}^{N} \sum_{j=1}^{N} d_{ij}\, \varepsilon_{m(i,j)}\, f_{ij} \quad (5)$$

Hash-chain provenance and action licence

Provenance is a hash chain on the observation that justifies u_t [3], not a dashboard badge. With cryptographic hash h and concatenation ‖,.

$$H_t = \mathrm{h}(H_{t-1} \parallel y_t \parallel t) \quad (6)$$

A mitigation command is released only after verification against the payload window y_1:t.

$$\mathrm{Ver}(H_t, y_{1:t}) = 1 \quad (7)$$

Two-sided FKF and companion FKL operators

Lead-time and disruption signals s pass through the two-sided Fourier–Kontorovich–Lebedev operator of the corpus [7]–[10], [24]. With modified Bessel kernel K_{iτ},.

$$\mathcal{F}_{KF}(s)(\tau) = \int_0^\infty s(x)\, K_{i\tau}(x)\, \frac{dx}{x} \quad (8)$$

Delayed multi-echelon events are handled by the documented time-shift identity [8], [12].

$$\big(s(t - t_0)\big)(\tau) = e^{-i\tau\, \varphi(t_0)}\, \mathcal{F}_{KF}(s)(\tau) \quad (9)$$

Exponential modulation records both a spectral-intensity change and a mark on residual feedback for a secure digital channel [13].

$$\big(e^{\alpha t}\, s(t)\big)(\tau) = \mathcal{F}_{KF}(s)(\tau + i\alpha) \quad (10)$$

The companion FKL operator [11] replaces the Kontorovich kernel by an L-kernel on the same half-line.

$$\mathcal{F}_{KL}(s)(\nu) = \int_0^\infty s(x)\, L_{i\nu}(x)\, dx \quad (11)$$

Residue-based resonance extraction [7] isolates a scale peak by a contour integral about a neighbourhood C_n of a suspected pole.

$$R_n = \frac{1}{2\pi i} \oint_{C_n} \mathcal{F}_{KF}(s)(\zeta)\, d\zeta \quad (12)$$

Streaming updates of (8) rest on sequential convergence in the testing-function space [25].

$$\langle s_n, \psi \rangle \to \langle \mathcal{F}_{KF}\, s, \psi \rangle \quad (13)$$

Calibrated predictor and quantum packing kernel

The control tower consumes a calibrated disruption probability built from the twin state, the FKF feature, and the provenance digest.

$$p_t = \sigma\left(w^T \phi(\hat{x}_t, \mathcal{F}_{KF}\, s_t, H_t)\right) \quad (14)$$

When the chosen action is unit-load-device (re)packing or disruption-aware assignment, the decision is a QUBO solved by quantum annealing [19], [21].

$$\min\ z^T Q\, z + q^T z \quad (15)$$

$$\text{s.t.}\ \ z \in \{0,1\}^n \quad (16)$$

The same assignment has an Ising form for analog annealers.

$$\mathrm{H}(s) = \sum_i h_i s_i + \sum_{i<j} J_{ij} s_i s_j \quad (17)$$

Every non-combinatorial action remains classical. The constrained planner that mixes twin loss, green cost, battery state-of-charge, and human/blockchain licence [6], [15], [18] is.

$$\min_u\ \mathcal{J}\left(\mathrm{L}(\hat{x}, u)\right) + \lambda J_g \quad (18)$$

$$u \in U(\mathrm{SoC}_t, H_t, \delta_t) \quad (19)$$

After execution, predictor parameters are rewritten from the residual.

$$\theta_{t+1} = \theta_t + \gamma_t \nabla_\theta\, \ell(y_t, \hat{y}_t) \quad (20)$$

Equations (1)–(3) implement the digital twin; (4)–(5) implement green logistics; (6)–(7) implement blockchain traceability; (8)–(13) implement FKF/FKL analysis; (14) is the predictor; and (15)–(19) implement quantum-or-classical mitigation under energy and governance constraints. Fig. 2 is the numerical sketch of (3), (14) and (18); Fig. 3 is the sketch of (8)–(12); Fig. Fig. 2–4 give S-curve sketches of those operators instead of the deleted summary tables.

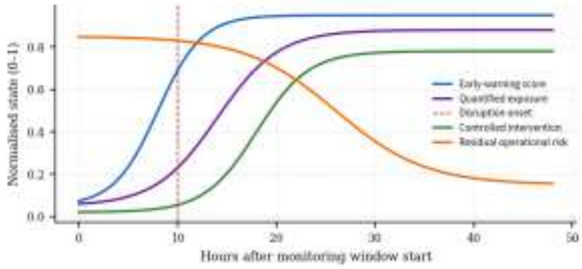

Fig. 2. S-curve trajectories of early-warning, exposure, intervention, and residual risk after a disruption window opens.

IV. READING OF THE ARCHITECTURE

A. From Mixed Streams to Risk Signatures

Identification starts when mixed telemetry, text, and operational observations become recognisable risk signatures. IoT platforms and intelligent transportation systems provide continuous data streams [14], [20], while AI–blockchain integration can improve the reliability, transparency, and traceability of these observations [33]. Power-line-carrier integrity monitoring [17] remains the reminder that physical tampering can erase those signatures before any model runs.

On the spectral side a disruption is a resonance, a shift, or a multi-scale change rather than an isolated timestamp. Multi-scale spectral analysis and residue-based resonance extraction provide mechanisms for detecting hidden periodic stress in hybrid-vehicle and logistics systems [37]. Shift-invariant FKF analysis of lead times seeks to preserve relevant spectral characteristics when disruptions introduce temporal delays without fundamentally changing the underlying pattern [38], [12]. The broader FKF resilience framework extends this concept by treating transform outputs as persistent monitoring signatures [39]. The FKL transform provides an alternative spectral representation for related classes of supply-chain signals [11]. Distributional extensions and sequential-convergence theorems then license the same operators on irregular and heavy-tailed streams [24], [25].

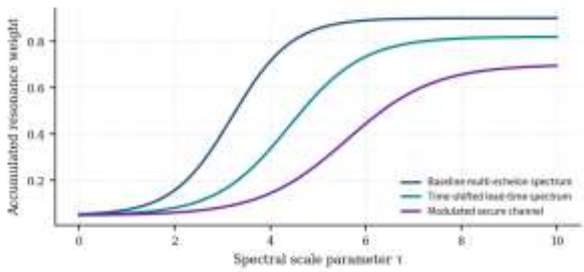

Fig. 3. Accumulated resonance S-curves in the FKF/FKL scale domain for baseline, delayed, and modulated signals.

Green logistics adds an identification axis that cost-and-service models usually omit. Green-AI research [32] indicates that environmental and regulatory risks may remain poorly represented when prediction systems emphasize only cost and service-related variables. Risk is therefore defined by the loss function an organisation actually optimises, not only by the detector it trains.

B. From Signature to Network Consequence

Assessment converts a detected signature into probability, severity, exposure, and propagation. Digital twins are particularly relevant because they permit alternative disruption scenarios to be simulated without physically exposing the supply network to failure [31]. The same reviews still report no stable resilience metric across studies, which limits how far any assessed score can be compared [23].

Spectral differentials of the distributional FKF transform ask how a lead-time perturbation moves a resilience signature [40], [24]. The resulting question is therefore not simply whether a spectral resonance exists, but how sensitive that resonance is to additional disturbances. Energy and mobility research supplies important physical constraints for this assessment stage. Battery chemistry, battery-management systems, and sizing approaches influence available transportation capacity following grid or charging disruptions, [18], [36]. Solar-assisted and hybrid vehicle architectures introduce additional energy-generation capabilities and consequently modify the feasible recovery space [16], [22]. If those energy limits are ignored, predicted last-mile recovery will look more feasible than the fleet can actually deliver.

C. From Score to Feasible Action

Mitigation is the step that turns a prediction into an operational intervention. Quantum-computing studies frame several mitigation problems as combinatorial optimization tasks involving transportation configuration, rerouting, scheduling, and unit-load-device packing under disrupted capacity, [19], [21], [35]. These approaches remain largely prospective, whereas conventional digital twins can already support counterfactual mitigation experiments and what-if analysis [31]. IoT therefore senses, AI predicts, and quantum search is reserved for the packing and scheduling kernels that exhaust classical heuristics [14].

Whether an automated action may fire is a governance question before it is a control question. AI–blockchain integration can provide an auditable record of decisions and the data underlying those decisions [33]. Industry 5.0 places the human operator at the center of exception handling, supervision, and ethical intervention rather than treating human involvement as merely a source of residual error [15]. Control-tower design therefore inherits the same concerns of latency, error, and decision authority that already appeared in early operator-interface work [34].

Exponential modulation of the FKF transform has been proposed as a marking method for secure digital supply-chain channels [13]. That marking matters whenever a mitigation decision is computed from a signal that an adversary could spoof.

D. Residual Monitoring and Model Rewrite

Monitoring closes the loop by measuring what an implemented action actually changed and by feeding that residual forward. Digital-transformation research emphasizes continuous visibility while identifying weaknesses in standardized resilience metrics [23]. Smart mobility and intelligent transportation systems generate extensive operational data from connected vehicles, charging infrastructure, and traffic-management systems that can support post-disruption learning [20]. Sustainability monitors then add emissions, energy use, and circularity to the usual delivery and cost KPIs [32].

Spectral monitors track frequency and scale drift instead of waiting for a KPI threshold to break [9]. Sequential-convergence results [25] become relevant when streaming observations are incorporated as mathematically consistent elements of the transform's testing-function framework. Detection, assessment, intervention, and learning then form one cycle rather than four disconnected reports.

V. GUIDANCE FOR SCHOLARS AND OPERATORS

Researchers should treat the corpus as a programme with unequal parts rather than as a flat reference list. Digital-twin, blockchain, Industry 5.0, and digital supply-chain reviews are most relevant when discussing managerial architecture, [15], [23], [31], [33]. The FKF/FKL series should be cited when the contribution is spectral [11]–[13], [24], [25]. Quantum papers are appropriate when the instance is combinatorial and current heuristics fail [35], [19], [21]. Battery-sizing and swipe-controller papers specify constraints or interfaces; they are not evidence that AI predicts supply-chain risk, [16], [17], [18], [22], [34], [36].

Practitioners should assemble the loop from the middle outward rather than from a full technology catalogue. Identification data quality and a twin of the two or three lanes that dominate disruption cost provide a practical starting point [31], [33]. Human override should be added before autonomy [15]. Electrified fleet state should be treated as a live risk input [20], [22]. Quantum kernels and specialised transforms stay on a research track until a controlled bake-off exists.

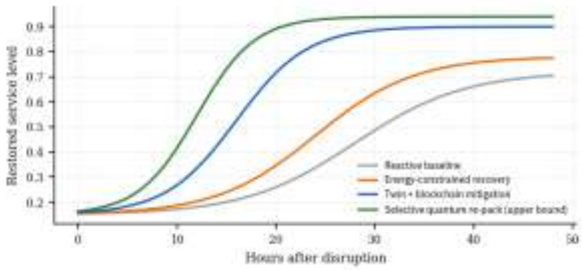

Fig. 4. Service-recovery S-curves under reactive, energy-constrained, twin–blockchain, and selective quantum-repack regimes.

VI. OPEN PROBLEMS AND NEXT MEASUREMENTS

A short list of research gaps still sits between this architecture and industrial use. Explainable AI is required so that managers and regulators can understand the reasoning behind risk predictions and recommended mitigation actions. Multi-tier visibility models should move beyond focal firms toward network-wide representations of cascading risk. Climate, social, and environmental variables remain only weakly represented in current predictive risk models.

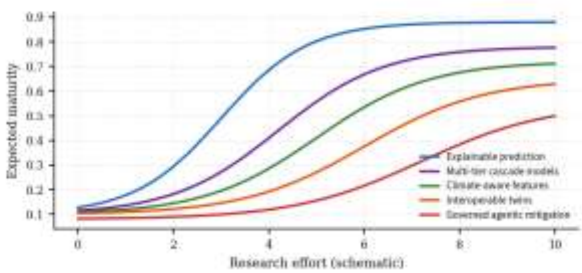

Fig. 5. Expected-maturity S-curves for five research priorities that still sit between the architecture and industrial use.

Cross-firm digital twins still lack shared data models and safe exchange protocols. Agentic AI offers a path from prediction toward semi-autonomous mitigation within operational, ethical, safety, and governance constraints. Autonomous chains will otherwise shed the human oversight that Industry 5.0 treats as non-negotiable.

VII. CONCLUSION

The paper has assembled one resilience architecture from predictive AI, IoT sensing, digital twins, blockchain, intelligent transportation, spectral analysis, and quantum optimisation, [14], [19]–[21], [23], [31]–[33], [35]. The PREDICT–MITIGATE approach transforms heterogeneous operational observations into risk estimates and subsequently into adaptive, constraint-aware mitigation decisions, with feedback continuously improving future predictions, [15], [25], [31], [39]. The findings emphasize that effective resilience depends not only on algorithmic accuracy but also on energy availability, transportation capacity, data integrity, cybersecurity, sustainability, and human oversight, [13], [16]–[18], [20], [22], [32], [34], [36]. FKF/FKL spectral techniques [11], [12], [24], [25] and quantum optimization [35], [19], [21] offer promising capabilities for multi-scale analysis and complex decision problems, although both require additional empirical and industrial validation. Supply-chain risk management is thereby recast as a predictive, adaptive, trustworthy, and only cautiously autonomous practice.

ACKNOWLEDGMENT

Editorial and production support from the International Journal of Creative and Open Research in Engineering and Management is gratefully acknowledged.

REFERENCES

[1] Sharma, R., Katukam, R., & Nagulapally, A. (2026). Bridging the Linear-Quadratic Gap: A Quantum-Classical Hybrid Approach to Robust Supply Chain Design. *arXiv preprint arXiv:2601.04095*.

[2] McKinsey & Company (2024). Digital twins: The key to unlocking end-to-end supply chain growth. *McKinsey Insights*.

[3] Wickremasinghe, G., et al. (2024). Uncertainty in Supply Chain Digital Twins: A Quantum-Classical Hybrid Approach. *arXiv preprint arXiv:2411.10254*.

[4] Various authors (2024). The role of digital twins in lean supply chain management: review

and research directions. *International Journal of Production Research*.

[5] Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, 57(3), 829–846.

[6] Ivanov, D. (2021). Digital supply chain twins: Managing the ripple effect, resilience, and disruption risks by data-driven optimization, simulation, and visibility. In *Handbook of Ripple Effects in the Supply Chain* (pp. 309–330). Springer.]

[7] S. M. Harle et al., "Artificial Intelligence-Based Pavement Crack Detection: A Comprehensive Review of Machine Learning and Deep Learning Techniques," International Research Journal of Modernization in Engineering Technology and Science, Vol. 8, pp. 50–69, July 2026.

[8] S. M. Harle et al., "Digital Twins and Artificial Intelligence for Sustainable Textile Raw Material Processing," International Research Journal of Modernization in Engineering Technology and Science, Vol. 8, pp. 14–30, July 2026.

[9] Heese, R., et al. (2026). Hybrid Quantum-Classical Optimization for Multi-Objective Supply Chain Logistics. *arXiv preprint arXiv:2602.05364*.

[10] S. M. Harle et al., "Artificial Intelligence Approaches for Strength Prediction and Optimization of Composite Concrete Mixtures: A Systematic Review and Future Research Framework," International Research Journal of Modernization in Engineering Technology and Science, Vol. 8, pp. 81–97, July 2026.

[11] A. Gulhane, "FKL Transform Key Properties, And Applications To Supply-chain Analysis," International Journal of Engineering Science and Advanced Technology, vol. 25, no. 12, pp. 596-605, Dec. 2025, doi: 10.64771/ijesat.2025.v25.i12.3816. [Online]. Available: https://doi.org/10.64771/ijesat.2025.v25.i12.3816

[12] A. Gulhane, "Expanded Treatment Of the Time-Shift Property Of FKF Transform With Supply-Chain Applications," International Journal of Engineering Science and Advanced Technology, vol. 25, no. 12, pp. 606-616, Dec. 2025, doi: 10.64771/ijesat.2025.v25.i12.3817. [Online]. Available: https://doi.org/10.64771/ijesat.2025.v25.i12.3817

[13] A. Gulhane, "The FKF Transform: Exponential Modulation Properties and Applications to Secure Digital Supply-Chain Networks," International Journal of Engineering Science and Advanced Technology, vol. 25, no. 12, pp. 617-623, Dec. 2025, doi: 10.64771/ijesat.2025.v25.i12.3818. [Online]. Available: https://doi.org/10.64771/ijesat.2025.v25.i12.3818

[14] A. Gulhane, "Internet of Things, Artificial Intelligence, and Quantum Computing: A Convergent Framework for Smart Logistics Ecosystems," International Journal of Engineering Science and Advanced Technology (IJESAT), vol. 24, no. 12, pp. 297-317, 2024, doi: 10.64771/ijesat.2024.v24.i12.3372. [Online]. Available: https://doi.org/10.64771/ijesat.2024.v24.i12.3372

[15] A. Gulhane, "Industry 5.0 and Intelligent Logistics: Transforming Supply Chain Operations through Human-Centric Automation," International Journal of Engineering Science and Advanced Technology (IJESAT), vol. 24, no. 12, pp. 287-296, 2024, doi: 10.64771/ijesat.2024.v24.i12.3371. [Online]. Available: https://doi.org/10.64771/ijesat.2024.v24.i12.3371

[16] A. Gulhane, "The Future of Vehicles: Solar-Powered Battery Electric Hybrid Vehicle Architecture," Tech Briefs Create the Future Design Contest, Automotive and Transportation, entry 10457, 2020. [Online]. Available: https://contest.techbriefs.com/2020/entries/automotive-transportation/10457

[17] A. Gulhane, "Power line carrier communication based anti-theft system," International Journal of Research in IT and Management (IJRIM), vol. 4, no. 12, pp. 1-11, 2014.

[18] A. Gulhane, "Battery sizing for plug-in hybrid electric vehicles — Formula hybrid," in Proceedings of the IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI), 2017, pp. 368-372, doi: 10.1109/ICPCSI.2017.8392317. [Online].

Available: https://doi.org/10.1109/ICPCSI.2017.8392317

[19] A. Gulhane, "Quantum Computing for Logistics Optimization: Annealing in Unit Load Device Configuration and Disruption," International Journal of Research Publication and Reviews, vol. 7, no. 6, pp. 4643-4648, Jun. 2026, doi: 10.55248/gengpi.07.0626.16a57. [Online]. Available: https://doi.org/10.55248/gengpi.07.0626.16a57

[20] A. Gulhane, "Smart Mobility and Intelligent Transportation Systems: Emerging Trends, Technologies, and Challenges," International Journal of Scientific Research in Engineering and Management (IJSREM), vol. 9, no. 11, Nov. 2025, doi: 10.55041/IJSREM53436. [Online]. Available: https://doi.org/10.55041/IJSREM53436

[21] A. Gulhane, "Quantum Computing in Transportation and Logistics: Current State, Industrial Applications, and Future Directions," International Journal of Scientific Research in Engineering and Management (IJSREM), vol. 9, no. 9, Sep. 2025, doi: 10.55041/IJSREM52469. [Online]. Available: https://doi.org/10.55041/IJSREM52469

[22] A. Gulhane, "Solar-Assisted Electric Mobility: Design Framework and Performance Assessment of Sustainable Hybrid Vehicle Architectures," International Journal of Engineering Research in Science and Technology, vol. 21, no. 3, pp. 362-368, 2025, doi: 10.56636/ijerst.2025.v21.i03.3594. [Online]. Available: https://doi.org/10.56636/ijerst.2025.v21.i03.3594

[23] A. Gulhane, "Supply Chain Resilience in the Era of Digital Transformation: A Systematic Literature Review and Research Agenda," International Journal of Engineering Research in Science and Technology, vol. 21, no. 4, pp. 1058-1068, 2025, doi: 10.56636/ijerst.2025.v21.i04.3812. [Online]. Available: https://doi.org/10.56636/ijerst.2025.v21.i04.3812

[24] A. Gulhane, "Distributional Extension of the FKF Transform and Its Relevance to Supply-Chain Systems," International Journal of Creative and Open Research in Engineering and Management, vol. 2, no. 8, Aug. 2026, doi: 10.55041/ijcope.v2i8.137. [Online]. Available: https://doi.org/10.55041/ijcope.v2i8.137

[25] A. Gulhane, "Sequential Convergence in the Testing Function Space of the Two-Sided FKF Transform," International Journal of Creative and Open Research in Engineering and Management, vol. 2, no. 8, Aug. 2026, doi: 10.55041/ijcope.v2i8.138. [Online]. Available: https://doi.org/10.55041/ijcope.v2i8.138

[26] Le Maître, O. P., & Knio, O. M. (2010). *Spectral Methods for Uncertainty Quantification: With Applications to Computational Fluid Dynamics*. Springer.

[27] Sharma, R., Katukam, R., & Nagulapally, A. (2026). Bridging the Linear-Quadratic Gap: A Quantum-Classical Hybrid Approach to Robust Supply Chain Design. *arXiv preprint arXiv:2601.04095*.

[28] McKinsey & Company (2024). Digital twins: The key to unlocking end-to-end supply chain growth. *McKinsey Insights*.

[29] Wickremasinghe, G., et al. (2024). Uncertainty in Supply Chain Digital Twins: A Quantum-Classical Hybrid Approach. *arXiv preprint arXiv:2411.10254*.

[30] Various authors (2024). The role of digital twins in lean supply chain management: review and research directions. *International Journal of Production Research*.

[31] A. Gulhane, "Digital Twin Technology for Building Resilient and Adaptive Global Supply Chains: A Review," International Research Journal of Modernization in Engineering Technology and Science, vol. 6, no. 12, 2024, doi: 10.56726/IRJMETS64992. [Online]. Available: https://doi.org/10.56726/IRJMETS64992

[32] A. Gulhane, "Artificial Intelligence Applications in Sustainable Logistics and Green Supply Chain Management: A Bibliometric Review," International Research Journal of Modernization in Engineering Technology and Science, vol. 6, no. 12, 2024, doi: 10.56726/IRJMETS65006. [Online]. Available: https://doi.org/10.56726/IRJMETS65006

[33] A. Gulhane, "Artificial Intelligence and Blockchain Integration for Enhancing Supply Chain Transparency, Traceability, and Resilience,"

International Research Journal of Modernization in Engineering Technology and Science, vol. 6, no. 12, 2024, doi: 10.56726/IRJMETS65016. [Online]. Available: https://doi.org/10.56726/IRJMETS65016

[34] A. Gulhane, "SWIPE CONTROLLER," International Journal of Research in Engineering and Applied Sciences (IJREAS), vol. 4, no. 12, pp. 1-7, 2014.

[35] A. Gulhane, "Navigating the Quantum Revolution in Logistics: Opportunities and Practical Applications in Supply Chain Management," International Journal of Engineering and Techniques (IJET), vol. 12, no. 3, pp. 553-556, 2026, doi: 10.29126/ijet.2026.v12.i3.553. [Online]. Available: https://doi.org/10.29126/ijet.2026.v12.i3.553

[36] A. Gulhane, "Recent Advances in Electric Vehicle Battery Technologies: Materials, Management Systems, and Sustainability Perspectives," International Journal of Scientific Research in Engineering and Management (IJSREM), vol. 9, no. 7, Jul. 2025, doi: 10.55041/IJSREM51198. [Online]. Available: https://doi.org/10.55041/IJSREM51198

[37] A. Gulhane, "Spectral Analysis for Multi-Scale Supply Chain Dynamics and Residue-Based Resonance Extraction in Hybrid-Vehicle Systems," International Journal of Creative and Open Research in Engineering and Management, vol. 2, no. 8, Aug. 2026, doi: 10.55041/ijcope.v2i8.141. [Online]. Available: https://doi.org/10.55041/ijcope.v2i8.141

[38] A. Gulhane, "Shift-Invariant Spectral Analysis of Multi-Echelon Supply-Chain Lead Times via the FKF Transform," International Journal of Creative and Open Research in Engineering and Management, vol. 2, no. 8, Aug. 2026, doi: 10.55041/ijcope.v2i8.136. [Online]. Available: https://doi.org/10.55041/ijcope.v2i8.136

[39] A. Gulhane, "Spectral Framework Based on the FKF Transform for Supply Chain Dynamics and Resilience," International Journal of Creative and Open Research in Engineering and Management, vol. 2, no. 8, Aug. 2026, doi: 10.55041/ijcope.v2i8.140. [Online]. Available: https://doi.org/10.55041/ijcope.v2i8.140

[40] A. Gulhane, "Spectral Differential Properties of the Distributional FKF Transform with Applications to Resilient Supply-Chain Systems," International Journal of Creative and Open Research in Engineering and Management, vol. 2, no. 8, Aug. 2026, doi: 10.55041/ijcope.v2i8.139. [Online]. Available: https://doi.org/10.55041/ijcope.v2i8.139

