

AI-Driven Digital Twin Intelligence for Predictive Supply-Chain Resilience and Adaptive Logistics

*Standalone AI theory, operational architecture, and reproducible synthetic evaluation design
Resilient Recovery*

Ruchita K. Ingole¹, Gupta A²

¹Assistant Professor, Department of Computer Engineering, G. H. RAISONI UNIVERSITY, Maharashtra, India, Email: ruchitaingole123@gmail.com

²Research Scholar

Abstract

Artificial intelligence is increasingly being positioned as an intelligence layer for supply-chain systems exposed to uncertain demand, variable lead times, disruptions, energy constraints, and incomplete information. This paper develops a standalone AI-centered framework in which machine-learning prediction, digital-twin synchronization, anomaly detection, resilience assessment, optimization, and operational authorization are treated as distinct but connected functions. The central contribution is an AI decision-admissibility model: an AI prediction is not interpreted as an executable command unless data quality, twin consistency, predictive confidence, operational feasibility, and authorization conditions are simultaneously satisfied. A state-space representation is introduced for demand, inventory, lead time, capacity, energy availability, and disruption risk. Mathematical constructs are developed for predictive error, anomaly intensity, disruption probability, confidence-aware inference, twin consistency, adaptive recovery, explainability, and an AI resilience index. The framework integrates the supplied literature on digital twins, sustainable logistics, AI, blockchain traceability, smart mobility, batteries, electric vehicles, quantum logistics, and supply-chain resilience. A synthetic evaluation structure is proposed so that comparative performance can be studied without fabricating field measurements. The resulting architecture establishes a pathway from telemetry to prediction, validation, optimization, authorization, execution, and learning while retaining human oversight and auditability.

Keywords: *Artificial intelligence, digital twin, predictive analytics, supply-chain resilience, anomaly detection, adaptive logistics, explainable AI, intelligent transportation, energy-aware mobility, decision admissibility*

1. INTRODUCTION

Modern supply chains can be viewed as cyber-physical networks in which physical inventory, transportation assets, energy resources, demand signals, and information systems interact continuously. Digital-twin concepts provide a computational representation of physical assets and processes so that observations can be compared with expected behavior and alternative operating states can be examined [11].

Artificial intelligence extends this representation by learning temporal and relational patterns from data. AI-oriented sustainable-logistics research has considered forecasting, routing, resource allocation, anomaly recognition, and green decision support [12]. When AI is combined with blockchain, analytical outputs can be connected with data provenance and traceability requirements [13].

The methodological problem is that a prediction and an action are not equivalent. A model can produce a plausible forecast while the twin is stale, input data are corrupted, uncertainty is high, or the proposed intervention violates vehicle,

battery, capacity, delivery-window, or authorization constraints. The proposed architecture therefore treats AI as a controlled intelligence layer rather than as unconditional command authority.

Earlier engineering work on PLC anti-theft protection and swipe-controller mechanisms illustrates that operational integrity and human interaction are part of system design [14]. Battery-sizing research supports the treatment of energy feasibility as an engineering constraint [15]. The smart-mobility setting broadens the problem from forecasting toward connected transportation and fleet coordination [19].

2. LITERATURE REVIEW AND RESEARCH GAP

Digital-twin research establishes a bridge between physical assets and computational analysis. In resilient supply chains, the twin can represent inventory, transportation, capacity, and process status while enabling scenario analysis and recovery assessment [23]. The main opportunity for AI is to convert the twin from a primarily representational artifact into a continuously learning inference environment.

AI for sustainable logistics broadens conventional planning by learning relationships among demand, transport conditions, operational capacity, and environmental constraints [12]. AI and blockchain integration provides a complementary integrity mechanism through provenance records for data, inference time, model version, and decision state [13].

Quantum-computing work in logistics suggests that combinatorial allocation and routing may be addressed by annealing after classical preprocessing [17]. A related study examines unit-load configuration and disruption [18]. Smart transportation and quantum reviews extend this application path [21].

The supplied FKF/FKL references provide mathematical context for transform operations, convergence, spectral analysis, and supply-chain dynamics [24]. Shift, modulation, differential, and FKL-property studies [25]-[32] support the broader research program. IoT-AI-quantum convergence [33], Industry 5.0 [34], solar-electric vehicle architecture [35], and resilience studies [36]-[38] broaden the interdisciplinary application domain.

The gap addressed here is the explicit separation of prediction, diagnosis, twin validation, feasibility, optimization, and authorization. A single black-box pipeline makes it difficult to identify whether a failure originated in sensing, learning, simulation, optimization, or execution.



Figure 1. AI-centered integration of the research themes

3. AI STATE-SPACE MODEL FOR LOGISTICS

A logistics network is represented by a time-indexed state vector whose components can be linked directly to telemetry or validated estimates. Let

$$\mathbf{z}_t = [D_t, I_t, L_t, C_t, E_t, R_t]^T$$

where demand, inventory, lead time, capacity, energy availability, and disruption risk form the principal state variables. The control vector contains dispatch, replenishment, routing, charging, or allocation decisions, while exogenous observations represent traffic, weather, supplier conditions, and other disturbances.

$$\mathbf{z}_{t+1} = F(\mathbf{z}_t, \mathbf{u}_t, \mathbf{e}_t) + \boldsymbol{\varepsilon}_t$$

The AI model learns an approximation of the state transition from a rolling temporal window.

$$\hat{\mathbf{z}}_{t+\Delta} = f_{\theta}(\mathbf{z}_{t-k:t}, \mathbf{u}_{t-k:t}, \mathbf{e}_{t-k:t})$$

Feature normalization can improve numerical conditioning when state variables use different scales.

$$x_i^* = \frac{x_i - \mu_i}{\sigma_i + \epsilon}$$

The temporal window retains process memory and is defined by

$$X_t = \{\mathbf{z}_{t-k+1}, \dots, \mathbf{z}_t\}$$

The window length k remains an empirically calibrated design parameter.



Figure 2. AI state-space representation

4. AI PREDICTION, ANOMALY DETECTION, AND DISRUPTION INFERENCE

Prediction quality is represented through explicit residuals rather than through a qualitative statement of accuracy. For a true state and a predicted state, define

$$e_t = \|\mathbf{z}_t - \hat{\mathbf{z}}_t\|_{\Sigma^{-1}}$$

For an individual component, a scale-normalized anomaly score is

$$a_{i,t} = \frac{|z_{i,t} - \hat{z}_{i,t}|}{\sigma_i + \epsilon}$$

A system-level anomaly intensity aggregates component scores.

$$A_t = \sum_{i=1}^n w_i a_{i,t}, \quad \sum_{i=1}^n w_i = 1$$

A disruption classifier can estimate the probability of an event inside a chosen forecast horizon.

$$p_t = \frac{1}{1 + \exp[-g_{\theta}(\mathbf{x}_t)]}$$

A confidence-aware forecast can be represented by

$$\hat{\mathbf{z}}_{t+\Delta} \pm q_{1-\alpha/2} \hat{\sigma}_{t+\Delta}$$

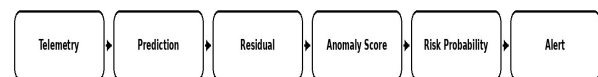


Figure 3. AI anomaly and disruption inference

5. AI-DIGITAL-TWIN SYNCHRONIZATION AND TRUST

A digital twin must remain sufficiently synchronized with the physical process to support meaningful inference. Let $\mathbf{y}_t$ denote telemetry and $h(\mathbf{z}_t)$ the observation predicted by the twin. The synchronization residual is

$$r_t = \|\mathbf{y}_t - h(\mathbf{z}_t)\|$$

A continuous consistency score can be mapped from the residual as

$$C_{\text{twin}} = \exp(-\lambda r_t)$$

The exponential mapping is a research construct rather than a universal standard; its threshold should be calibrated against measurement uncertainty and twin fidelity. Each inference can be associated with a provenance tuple containing source, timestamp, preprocessing state, model identifier, version,

inference horizon, confidence, twin consistency, and authorization state.

Blockchain or integrity-oriented records can preserve chronology across participating organizations [13]. The twin should therefore be treated as a state-estimation and scenario-analysis layer rather than only as a visualization [11].

When twin consistency falls below a calibrated threshold, automatic execution can be suspended while observation and diagnosis continue. This creates a controlled degraded mode in which intelligence remains available but execution authority is withheld.



Figure 4. Digital-twin synchronization and provenance path
6. AI DECISION-ADMISSIBILITY AND ADAPTIVE LOGISTICS

The central operational construct is an admissibility gate between AI recommendation and execution. Let predictive confidence, twin consistency, energy feasibility, data quality, and authorization be represented by C_{AI} , C_{twin} , E_{feas} , P_{data} , and H_{auth} .

$$\mathcal{A}(t) = \begin{cases} 1, & C_{AI} \geq \gamma_1, C_{twin} \geq \gamma_2, E_{feas} \geq \gamma_3, P_{data} \geq \gamma_4, H_{auth} = 1, \\ 0, & \text{otherwise.} \end{cases}$$

If any condition fails, the output remains a recommendation or queued decision rather than an executed command. This prevents a high-confidence prediction from bypassing engineering constraints.

$$J(\mathbf{u}) = w_1 J_{service} + w_2 J_{cost} + w_3 J_{energy} + w_4 J_{risk} + w_5 J_{emission}$$

$$E_{req}(\mathbf{u}) \leq E_{avail}(t) + E_{harvest}(t) - E_{reserve}$$

Adaptive recovery then searches within the feasible action set.

$$\min_{\mathbf{u} \in U} [J(\mathbf{u}) + \lambda_R R(\mathbf{u})]$$

Energy-aware dispatch is consistent with the vehicle and battery context developed in the supplied work [15], [20].

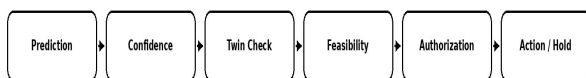


Figure 5. AI decision-admissibility and adaptive recovery
7. EXPLAINABLE, HUMAN-CENTRIC, AND TRACEABLE AI

Operational AI needs a mechanism through which changes in recommendations can be inspected. Let ϕ_i represent the contribution of feature i to a local prediction. A generic additive explanation is

$$\hat{y} = \phi_0 + \sum_{i=1}^n \phi_i$$

The expression is a generic explanatory decomposition; feature attribution, sensitivity analysis, counterfactual explanation, or rule extraction may be selected according to model type. Human-centric Industry 5.0 emphasizes intelligent systems that support workers and preserve meaningful control [34].

The proposed architecture therefore carries H_{auth} into the decision gate. AI may detect, predict, compare, and explain candidate actions while an explicit authorization stage remains visible.

Traceability extends to model lifecycle management. A decision record should identify the training-data period, model version, preprocessing configuration, inference timestamp, confidence, twin consistency, action candidate, and authorization outcome. This is relevant to connected transportation and smart mobility [19].

IoT and AI convergence emphasizes the need for a continuous sensing-to-intelligence loop [33]. Model drift can be monitored using a distance between training and live feature distributions and can trigger controlled recalibration rather than silent degradation.



Figure 6. Human-centric explainable-AI decision chain
8. AI RESILIENCE INDEX AND SYSTEM PERFORMANCE

To connect intelligence quality with operational resilience, define A_t for anomaly awareness, P_t for predictive reliability, T_t for twin consistency, D_t for adaptive decision capability, and E_t for energy feasibility. A composite research index is

$$\mathcal{R}_{AI}(t) = w_A A_t + w_P P_t + w_T T_t + w_D D_t + w_E E_t$$

$$w_A + w_P + w_T + w_D + w_E = 1, \quad 0 \leq \mathcal{R}_{AI}(t) \leq 1$$

The index is a research construct rather than an industry standard. It should be validated against service-level degradation, recovery time, inventory exposure, emergency transport, energy use, and post-disruption stability.

$$R_Q(t) = \frac{Q(t) - Q_{min}}{Q_0 - Q_{min}}$$

This distinction matters because rapid detection and rapid recovery are separate outcomes. A model may identify a disruption quickly while still being unable to produce an admissible recovery action.

Resilience studies supplied for this work motivate the focus on recovery and adaptation [36]. Internal and external supply-chain complexity further motivate the resilience construct [37]. Automotive-battery considerations motivate the energy component [38].

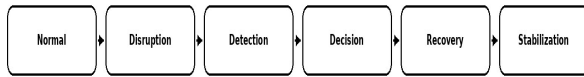


Figure 7. AI resilience trajectory

9. ENERGY-AWARE AI FOR SMART MOBILITY AND LOGISTICS

AI-enabled logistics increasingly interacts with electric mobility, charging infrastructure, and renewable power. For vehicle v , state of charge is

$$SoC_v(t) = \frac{E_v(t)}{E_v^{max}}$$

A solar-assisted energy contribution can be represented by

$$E_{PV}(t) = \eta_{PV} A_{PV} G_t PR(t)$$

The AI layer can predict energy availability and coordinate routing, charging, and delivery requirements. This connects battery-sizing work [15] with later battery-technology studies [20]. Smart mobility supplies the transportation context [19]. Solar-assisted architecture provides the renewable-energy contribution [22].

A fleet-level feasibility condition is

$$\sum_{v \in V} E_{req,v}(\mathbf{u}_v) \leq \sum_{v \in V} E_{avail,v}(t)$$

Extensions can incorporate battery ageing, temperature, charger queueing, renewable intermittency, and depot limits. The vehicle-architecture reference supports coupling vehicle and energy variables [35].



Figure 8. Energy-aware AI coordination

10. AI WITH OPTIMIZATION AND QUANTUM LOGISTICS

AI prediction and combinatorial optimization solve different parts of the decision problem. AI can estimate uncertain quantities such as demand, arrival time, disruption probability, and energy consumption. The optimizer then finds a feasible configuration. The supplied logistics work supports this downstream interpretation [17].

A binary optimization form is

$$\min_{\mathbf{x} \in \{0,1\}^n} \left[\sum_i c_i x_i + \sum_{i < j} Q_{ij} x_i x_j \right]$$

AI predictions can alter the coefficients. A predicted disruption probability can increase the penalty of a fragile route, while forecast demand can modify assignment requirements. Quantum annealing may be considered after classical feature preparation and constraint encoding [18].

A broader transportation-quantum review supports the distinction between predictive intelligence and downstream optimization [21]. IoT-AI-quantum convergence provides the systems context [33]. Any claim of quantum advantage requires controlled benchmarking and is not asserted by the conceptual framework.

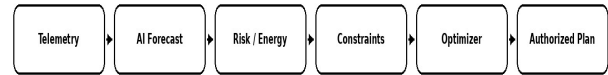


Figure 9. AI-to-optimization pipeline

11. SYNTHETIC CASE-STUDY DESIGN AND EVALUATION

The proposed evaluation uses a reproducible synthetic multi-echelon network containing suppliers, distribution centers, transport links, customer demand nodes, and an energy-constrained vehicle fleet. Demand contains trend and stochastic components; controlled disruptions are introduced through lead-time increases, capacity reductions, supplier interruption, and energy scarcity.

Four configurations can be compared under identical realizations: M1 conventional forecasting, M2 machine-learning forecasting, M3 AI coupled with a digital twin, and M4 AI plus digital twin plus admissibility-controlled adaptive decision support.

Mean absolute error is

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$$

Root mean square error is

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$$

Additional metrics should include precision, recall, F1, disruption detection delay, service-level loss, recovery time, energy consumption, and false-admissibility count. The case-study logic is consistent with the resilience and adaptive-supply-chain framework in the supplied literature [23].

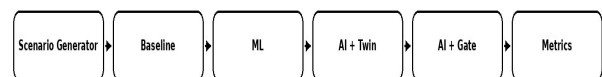


Figure 10. Reproducible synthetic evaluation design

12. EXPECTED ANALYTICAL RESULTS AND DISCUSSION FRAMEWORK

This manuscript is a theoretical framework rather than a report of a completed field experiment; therefore numerical performance values are not fabricated. Instead, evidence should be defined through measurable hypotheses. A predictor should

reduce held-out error or improve uncertainty calibration relative to a baseline under the same data budget.

The digital twin should contribute measurable synchronization value. If AI-plus-twin does not improve anomaly discrimination, recovery timing, or decision quality relative to AI alone, the cause should be investigated through twin fidelity, sensor coverage, or model mismatch.

The admissibility gate should reduce false-authorized actions, although a possible trade-off is an increase in held or deferred recommendations when confidence or consistency is low. That trade-off is itself a measurable operational property.

Energy-aware AI should be evaluated using reserve compliance, charging events, and energy consumption, not travel time alone. Renewable generation should be represented with uncertainty rather than as a deterministic resource [22].

Optimization performance should be separated from prediction performance. The staged architecture makes these interactions observable. An ablation plan should remove the twin, provenance/explainability, admissibility gate, and energy constraints in separate experiments.

13. DISCUSSION, LIMITATIONS, AND FUTURE VALIDATION

The framework changes the role of AI from an isolated forecasting component to a structured intelligence layer in a cyber-physical logistics system. State representation makes operational context explicit, anomaly detection identifies deviations, digital-twin comparison tests physical consistency, and the admissibility gate prevents prediction from becoming automatic authority.

The architecture also connects resilience and sustainability. A recovery action may reduce delivery delay while increasing emergency mileage, energy use, or battery stress. Another action may conserve energy while increasing inventory exposure. Multi-objective analysis is therefore necessary when mobility and energy resources are coupled.

The supplied literature provides the interdisciplinary basis for this architecture. Digital twins, AI, blockchain, smart mobility, batteries, quantum logistics, and resilience establish the application setting [11]. The mathematical FKF/FKL studies [24]-[32] remain contextual rather than central to this AI manuscript.

Limitations include dependence on data quality, distribution shift, model calibration, twin fidelity, and application-specific constraints. The resilience index requires empirical calibration. Human authorization also needs controlled evaluation because operator behavior can affect the effective decision loop.

Future validation should use real logistics telemetry, controlled disruptions, cross-site datasets, and long-duration drift measurements. Human-in-the-loop studies should test whether explanations improve review quality. Energy experiments should include battery ageing, charging availability, and renewable intermittency.

14. CONCLUSION

This paper developed an AI-centered digital-twin framework for predictive supply-chain resilience and adaptive logistics. The model represents logistics as a dynamic operational state, applies an AI prediction operator, quantifies residual and anomaly behavior, estimates disruption probability, evaluates digital-twin consistency, incorporates energy and operational feasibility, and separates recommendation from authorization.

The proposed AI resilience index provides a structured research construct for connecting intelligence quality with adaptive recovery, while the explainability and provenance layers support traceability and human-centric operation. AI predictions can supply informed parameters to classical or quantum optimization without conflating prediction with optimization.

The principal theoretical contribution is the explicit separation of intelligence, diagnosis, twin validation, feasibility, optimization, and authorization. This separation allows future empirical studies to identify where performance changes originate and to measure false-admissibility events directly.

The architecture can serve as a foundation for experimental studies using real-time logistics, intelligent transportation, battery, renewable-energy, and disruption datasets. Its practical value should be established through controlled validation rather than assumed from the conceptual formulation alone.

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