



COGNITIVE LOGISTICS ORCHESTRATION: A MODEL-BASED ARCHITECTURE FOR PREDICTIVE ALIGNMENT AND SYSTEMIC RESILIENCE IN VOLATILE SUPPLY NETWORKS

Simon Suwnazy Dzureke

Department of Business Administration,
Colorado Technical University,
Colorado Springs, CO, USA,
<https://orcid.org/0009-0005-4137-9461>

Semefa Elikplim Dzureke

Razak Faculty of Technology and Informatics,
Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia,
<https://orcid.org/0009-0007-6480-6520>

Evans Dzureke

Department of Health and Biomedical Sciences,
University of Texas Rio Grande Valley, Texas, USA,
<https://orcid.org/0009-0005-1794-0298>

Franklin Manasey Dzureke

Department of Business Administration,
University of Ghana, Legon, Koforidua, Eastern Region, DL,
<https://orcid.org/0009-0000-5298-701X>
simon.dzureke@gmail.com

Corresponding author: **Simon Suwnazy Dzureke**

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Abstract

The modern logistics network is a volatile, adaptive system. The disruptions spread quickly across the connected nodes. This highlights the weaknesses of supply chains optimized for efficiency but lacking execution speed and predictive acuity. This study builds and tests a Model-Based Risk Management (MBRM) system that leverages real-time sensing, predictive modeling, and regulated autonomous execution to transform information velocity into operational resilience. The sequential mixed-methods design integrates the results from ten multinational firms with a 2000-step, 1000-agent simulation described in the Overview, Design concepts, and Details (ODD) protocol. Empirical results demonstrate that Predictive Alignment (PA), Systemic Resilience (SR), and Signal Fidelity (SF) are positively associated with Value Orchestration Efficiency (VOE), whereas shorter decision-to-execution latency decreases volatility. Simulation results show that integrated cognitive architectures exhibit higher VOE, recover 7X faster, and reduce predicted revenue-volatility variance by 90+% in the presence of compound shocks. Qualitative insights indicate that responsible deployment depends on regulated autonomy, interpretability methods and specialized organizational roles. This study conceptualizes predictive intelligence as an operational tool to anticipate, absorb, and respond to disturbances in perpetually variable supply networks.

Keywords: Predictive logistics, resilience engineering, digital twins, autonomous orchestration, **supply-chain volatility**, agent-based modeling

1. INTRODUCTION

1.1. Logistics Volatility and the Predictive Imperative

Global logistics networks have become tightly interdependent, complex adaptive systems, making them increasingly vulnerable to disruption at multiple levels (Wycisk et al., 2008). The stability that once enabled lean, just-in-time (JIT) inventory regimes has steadily eroded owing to geopolitical conflict, climate-driven extremes, infrastructure fragility, demand volatility, and persistent labor shortages (Dzreke & Dzreke, 2025a). Under these conditions, reliance on retrospective analytics built around batch processing, offline reporting, and manual review introduces decision latency just as disruptions spread fastest (Biswas & Sen, 2016). As the gap between environmental change and managerial response widens, localized disturbances increasingly risk cascading into systemic failures (Wright et al., 2007). Recent digital twin research suggests that effective real-time decision-making depends not only on faster computation but also on maintaining temporal alignment among data refresh, decision generation, and evolving system conditions (Tolia & Ponis, 2026). This reinforces the need for continuous predictive alignment, in which signals from sensors, transactional systems, logistics platforms, and external feeds are synthesized to detect emerging risks before they escalate (Nwokocha et al., 2025). However, prediction alone does not guarantee timely intervention. Decision-makers may assign inappropriate weight to algorithmic recommendations when private information shapes their judgments (Balakrishnan et al., 2025), and algorithm aversion can diminish the willingness to rely on Artificial Intelligence (AI), even when its demonstrated performance exceeds human benchmarks (Bockstedt & Buckman, 2025). Therefore, contemporary logistics environments require intelligence that senses, simulates, and supports intervention rather than merely recording disruptions after the fact (Seyedan & Mafakheri, 2020; Ghosh & Fernandes, 2026).

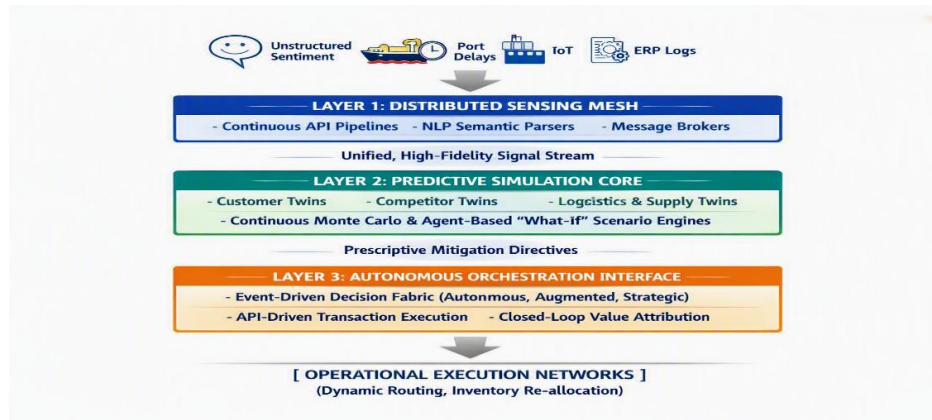


Figure 1. Systemic Transition From Recovery to Preventative Orchestration

Note. The figure illustrates the transition from reactive disruption recovery to continuous, model-based preventive orchestration through integrated sensing, simulation, autonomous intervention, and feedback.

1.2. Problem: The Resilience-Efficiency Paradox in Modern Logistics

Modern supply chains often prioritize short-term efficiencies over long-term resilience. Inventory minimization, supplier consolidation, high asset utilization, and lowest-cost routing can reduce costs under stable conditions while removing buffers and alternative pathways needed to absorb disruptions (Dzreke & Dzreke, 2025a). This vulnerability becomes more pronounced when analytics are fragmented across organizational silos, limiting visibility into the interacting risks (Tang, 2006). Srai et al. (2021) emphasized the importance of understanding supply networks at the system level, while digital twin research identified connectivity, visibility, agility, integration, and intelligence as essential foundations for real-time supply chain modeling (Wang et al., 2022). Therefore, the challenge is not merely accessing predictive technology. Organizations must consolidate distributed signals, interpret their interactions, and translate them into timely decisions. Conventional risk management approaches may identify individual disturbances but fail to capture the interdependencies through which disruptions propagate (Qazi et al., 2017). Even when predictive recommendations are available, human judgment, trust, and willingness to rely on algorithms determine whether people act on them (Balakrishnan et al., 2025; Bockstedt & Buckman, 2025).

1.3. Solution: The Model-Based Risk Management System

The Model-Based Risk Management framework addresses this problem by linking real-time observations, dynamic simulations, risk evaluations, governed interventions, and feedback. Distributed sensing meshes ingest and standardize heterogeneous logistics data to establish network-wide situational awareness (Sahoo et al., 2026). The Predictive Simulation Core transforms these signals into scenarios and evaluates their implications across inventories, capacities, transportation networks, supplier portfolios, and customer service performance (Ivanov & Dolgui, 2020). The Autonomous Orchestration Interface then converts the model outputs into bounded interventions that align with

predefined strategic constraints, extending the self-optimizing logic identified by Dzreke (2026a) and the self-tuning balance between efficiency and flexibility described by Dzreke and Dzreke (2026b). The proposed autonomy was intentionally limited. AI-enabled interventions can raise legal, compliance, and accountability concerns, particularly when systems operate rapidly or exercise discretionary authority (Kramer, 2024; Kolt, 2026). Therefore, the framework assigns decision rights based on risk, sets intervention thresholds, provides escalation paths, and preserves process auditability. Lower-risk, reversible actions may be automated, whereas consequential or irreversible decisions require appropriate oversight. This approach extends intelligent digital twin research beyond monitoring and simulation to a closed loop of sensing, prediction, intervention, and feedback (Ivanov, 2023; Khan, 2026).

1.4. Research Scope, Core Questions, and Outline

This study evaluated the theoretical foundations, mathematical formulation, and operational performance of a model-based risk management framework. Three questions guide the inquiry: how to integrate heterogeneous signals in real time to predict logistics disruptions; how mathematical mechanisms can balance short-term efficiency and long-term resilience; and how closed-loop prescriptive risk management affects operational stability during major supply network shocks. These questions integrate logistics resilience, predictive analytics, digital twin simulations, and autonomous decision orchestration. Forecasting research shows that predictive information can support procurement, production, supply portfolio selection, allocation, and customer order fulfillment during prolonged disruptions (Yang & Peng, 2023). Building on this work, the present study examines whether predictive intelligence can continuously sense system conditions, simulate disruption trajectories, evaluate resilience-efficiency trade-offs, and orchestrate bounded interventions using feedback loops. Consequently, this study treats predictive logistics resilience as a sociotechnical decision problem in which analytical speed, human judgment, and accountable autonomy must work together.

2. LITERATURE REVIEW

2.1. From Static Optimization to Complex Adaptive Logistics Systems

Traditional logistics management often treats supply networks as predictable systems, with costs, capacities, flows, and inventories optimized using mathematical models (Mallesham, 2024). Complexity economics offers a different perspective, recognizing heterogeneous agents that learn, adapt, and interact to produce outcomes that cannot always be inferred from individual components (Schiffling et al., 2020). This perspective is particularly relevant to logistics because disruptions can cascade across suppliers, inventories, transportation capacity, and demand, producing ripple effects that conventional optimization may not fully capture (Dolgui et al., 2017; Ivanov, 2021). Ghadge et al. (2021) demonstrated how simultaneous and prolonged disruptions propagate through interconnected supply chain structures. Therefore, resilience requires more than efficiency; it depends on adaptability, visibility, and the ability to reconfigure when conditions change (Bruckler et al., 2024).

2.2. The Evolution of Logistics Analytics: Descriptive to Prescriptive

Logistics analytics has evolved from retrospective reporting to predictive and prescriptive decision support (Husnain, 2026). Earlier systems relied heavily on manual records and scheduled reporting, whereas Supply Chain 4.0 introduced automated data acquisition, predictive models, and digital platforms (Tipi, 2021). However, Supply Chain 4.0 should not be characterized solely by scheduled batches, as contemporary systems can combine batch, event-driven, and streaming data ingestion (Oluyisola et al., 2021). Cognitive networks extend this progression toward real-time digital twins and connected decision-making processes. Predictive models estimate what may happen, whereas prescriptive analytics address the actions that should follow (Smyth et al., 2024; Lepenioti et al., 2019). This transition is not purely technological. Managers may interpret or weigh algorithmic recommendations differently when they have private information, creating friction in human-artificial intelligence (AI) collaboration (Balakrishnan et al., 2025). Closed-loop execution also raises legal, compliance, and accountability concerns when AI systems influence operational decisions (Kramer, 2024).

Table 1. Comparison of Logistics Evolution Paradigms

Dimension	Legacy Logistics	Supply Chain 4.0	Cognitive Networks
Data ingestion	Manual, paper-based (Herold et al., 2021)	Hybrid batch, automated, and streaming (Oluyisola et al., 2021)	Continuous connected data flows
Analytical model	Retrospective reporting (Groschopf et al., 2021)	Predictive models (Iftikhar et al., 2022)	Real-time digital twins (Wang et al., 2022)
Execution style	Human-initiated actions (Calatayud et al., 2018)	Closed-loop decision support (Dey, 2022)	Governed autonomous action
Risk approach	Reactive recovery plans (Xu et al., 2022)	Scenario-planning models (Xu et al., 2022)	Proactive resilience (Dey, 2022)

The progression shown in Table 1 is conceptual, not inevitable. Cognitive networks require substantial capital investment, system integration, specialized capabilities, and organizational changes. Digital twinning studies also report high financial and time costs that may constrain adoption, particularly for firms with limited resources (Yun et al., 2024).

2.3. Digital Twins, Internet of Things Telemetry, and Real-Time Visibility

The growth of the Internet of Things (IoT), cloud platforms, tracking technologies, and edge computing has increased the volume and timeliness of logistics data collection. Digital twins can enhance connectivity, visibility, agility, integration, and intelligence in real-time supply chain environments (Wang et al., 2022). Research also emphasizes transparency, trust, and resilience in logistics digital-twin applications (Le & Fan, 2023), while integrated internal and external data can support synchronized modeling (Zaidi et al., 2024). Emerging research has further linked digital twins with machine learning (ML), natural language processing (NLP), and multi-agent modeling (Ivanov, 2026).

In this study, a resilient logistics twin is considered a conceptual extension rather than an established, standardized term. A conventional digital twin may support broad operational monitoring and optimization, whereas a resilient logistics twin focuses on disruption detection, stress testing, alternative response pathways, and resilience-efficiency trade-offs. However, its development depends on data quality, integration capability, investment, and implementation time (Yun et al., 2024).

2.4. Quantitative Risk Assessment and Decision Science in Supply Chain Management

Quantitative risk research increasingly focuses on interactions, propagation, and system behavior, rather than isolated failure points. Ghadge et al. (2013) provided a strong foundation for a holistic quantitative approach to supply chain risk modeling, while Ghadge et al. (2021) examined the ripple effects of long-term, simultaneous disruptions. Decision science extends this logic through stochastic optimization, Bayesian reasoning, simulation, reinforcement learning (RL), and adaptive control (Shahnawaz & Safder, 2025; Liang, 2025). Therefore, the methodological shift is toward continuously updating the decision environment as new evidence emerges (Browning et al., 2023; Schoenherr et al., 2023).

2.5. Identification of the Research Gap

The literature has advanced in artificial intelligence prediction, IoT visibility, digital twins, simulation, and prescriptive analytics; however, these capabilities remain only partially integrated (Belhadi et al., 2022; Smyth et al., 2024). An unresolved issue is how sensing, simulation, risk evaluation, and intervention can function as a single connected architecture. Human-algorithm friction may weaken predictive alignment (Balakrishnan et al., 2025), whereas legal and compliance requirements constrain unrestricted autonomous execution (Kramer, 2024). The proposed framework addresses this gap by linking predictive intelligence with governed interventions, feedback, and measurable resilience outcomes.

3. THEORETICAL FRAMEWORK

3.1. Architectural Design of the Model-Based Risk Management System

The model-based risk management (MBRM) system is conceptualized as a three-layer cognitive architecture that links continuous environmental sensing, predictive simulation, and governed operational intervention. The architecture is grounded in the premise that resilience cannot be achieved through isolated forecasting or retrospective assessment; it requires an integrated capability that continuously transforms information into anticipatory decisions and adaptive responses. This position aligns with research on digital supply chain twins, which identifies connectivity, visibility, agility, integration, and intelligence as the foundational characteristics of digitally enabled networks (Wang et al., 2022). This also aligns with the literature describing intelligent digital twins as human-artificial intelligence (AI) decision-support systems that monitor, predict disruptions, stress-test, enable event-driven responses, and support organizational learning (Ivanov, 2026). To address interpretability concerns increasingly emphasized in cognitive logistics research, the decision-support layer incorporates model-explanation techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations). It aligns with the NIST AI Risk Management Framework (NIST AI RMF) to ensure transparency in high-stakes operational environments.

Layer 1, the Distributed Sensing Mesh (DSM), provides the architecture's information-acquisition foundation. It integrates structured operational data, including inventory positions, shipment records, customer orders, transportation costs, supplier performance, and capacity utilization, with external signals, such as port congestion, weather conditions, fuel prices, regulatory changes, and market sentiment. Application programming interface (API) pipelines, message brokers, streaming infrastructure, and natural language processing (NLP) mechanisms transform these heterogeneous observations into standardized signaling environments. This layer's theoretical significance lies in its ability to reduce temporal and informational fragmentation between environmental change and organizational perception. Research on digital twins similarly emphasizes the need for transparent, timely, and integrated information architectures to support effective decision-making (Le & Fan, 2023). Because this layer provides the foundational input to a closed-loop autonomous system, its integrity must be protected against adversarial data injection; accordingly,

the sensing mesh aligns with established AI security standards, such as the NIST AI RMF and ISO/IEC 42001:2023 (Artificial Intelligence Management System Standard).

Layer 2, the Predictive Simulation Core (PSC), converts standardized signals into dynamic representations of the logistics system. The MBRM conceptualizes three interacting representations: a Customer Twin (CT) that models purchasing patterns and service requirements; a Competitor Twin (CoT) that represents competitors' responses and market behavior; and a Logistics Twin (LT) that models transportation flows, port conditions, carrier capacity, inventory positions, and supply network constraints. These representations support continuous Monte Carlo (MC), discrete event (DE), and agent-based (AB) scenario analyses, enabling the estimation of alternative future states before disruption occurs. Digital twin research shows that simulation-based representations support stress testing and resilience improvement by revealing the consequences of alternative operating conditions (Tiwari et al., 2023). To ensure reproducibility, the simulation's agent-based components follow the Overview, Design, and Details (ODD) protocol, which is the field standard for documenting agent-based models in supply chain science.

Layer 3, the Autonomous Orchestration Interface (AOI), translates the simulation outputs into bounded operational interventions. The architecture distinguishes between autonomous, human-augmented, and human-led decisions based on risk, reversibility, financial exposure, and strategic consequences. Low-risk interventions, such as rerouting shipments around localized congestion, can be executed automatically via APIs. Medium-risk decisions, such as reallocating inventory between regional facilities, can be presented to managers with predicted outcomes and confidence estimates. High-consequence interventions, including supplier restructuring and contractual changes, remain subject to executive decisions. Graduated autonomy balances operational speed and governance. Research on AI-enabled prescriptive analytics emphasizes the need to connect algorithmic recommendations to organizational decision-making processes (Schäfers et al., 2024). Dzreke and Dzreke (2026c) reinforce this logic by conceptualizing self-tuning supply chain operations in which predictive intelligence, adaptive control, and governed execution operate within an integrated decision architecture. To prevent automated actions from becoming opaque "black boxes," the system logs lower-risk autonomous decisions using a responsibility-attribution model that preserves full traceability. Because coordinated interventions rely on autonomous execution, the interface's governance assumptions reflect emerging regulatory perspectives showing that conventional agency law is insufficient for autonomous systems operating at high speed and scale (Kolt, 2025; Kramer, 2024).

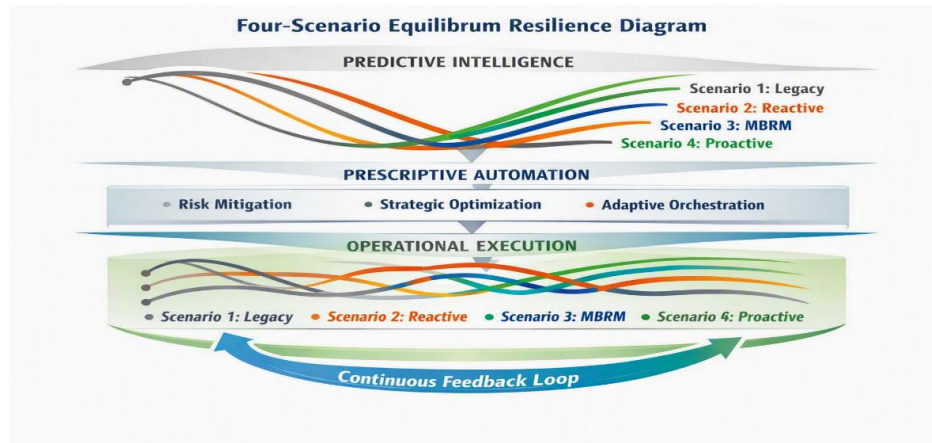


Figure 2. Three-Layered System Architecture of the MBRM Framework

Note. The framework conceptualizes sensing, simulation, prescriptive decision-making, and controlled execution as an integrated closed-loop architecture.

3.2. Mathematical Formalization of Systemic Resilience and Volatility Metrics

The theoretical architecture is operationalized through three constructs: Predictive Alignment (PA), Systemic Resilience (SR), and Value Orchestration Efficiency (VOE). PA measures the degree of alignment between simulated future logistics states and the subsequently observed states. Let $x_{t+\tau}$ represent the observed system state at future time $t + \tau$, $\hat{x}_{t+\tau|t}$ represent the state predicted at time t , w_τ denote a temporal discount factor, and H represent the prediction horizon. Predictive Alignment can be expressed as

$$PA_t = 1 - \frac{\sum_{\tau=1}^H w_\tau \|x_{t+\tau} - \hat{x}_{t+\tau|t}\|_2}{\sum_{\tau=1}^H w_\tau \|x_{t+\tau}\|_2}$$

Values approaching 1 indicate a stronger correspondence between the predicted and realized states. Because human-

algorithm collaboration can be affected by algorithm aversion, prediction quality may not always translate directly into better intervention timing (Balakrishnan et al., 2025). SR measures the network's capacity to absorb disruption while maintaining critical performance and recovering toward its baseline (Wan et al., 2021). Let $P(t)$ denote the system performance at time t , P_0 the pre-disruption baseline, t_d the disruption onset, and t_r the recovery point. A normalized resilience measure can be represented by the accumulated performance maintained across the disruption-recovery interval as follows:

$$SR = \frac{1}{t_r - t_d} \sum_{t_d}^{t_r} \frac{P(t)}{P_0} dt - \lambda C_d$$

The cost penalty term λC_d is a novel adaptation tied to absorptive, adaptive, and restorative resilience capacities (Bruckler et al., 2024). VOE captures the risk-adjusted value generated by coordinated interventions relative to the volatility required to achieve this. Excessive efficiency can amplify fragility, reinforcing the need to evaluate performance through a joint efficiency-resilience lens (Dzreke & Dzreke, 2025b). Because VOE rely on autonomous execution, their governance assumptions reflect emerging regulatory concerns (Kolt, 2025; Kramer, 2024).

3.3. Theoretical Hypotheses (H) Formulation

H1 posits that higher Predictive Alignment (PA) is positively associated with Value Orchestration Efficiency (VOE). H2 posits that Systemic Resilience (SR) positively moderates the PA-VOE relationship, consistent with evidence that predictive capabilities become strategically useful when linked to resilience-oriented response mechanisms (Kipper, 2024). H3 posits that integrating physical, financial, and informational flows through a unified cognitive architecture reduces decision-to-execution latency compared with siloed platforms (Ding et al., 2026). H4 posits that closed-loop autonomous execution reduces revenue volatility during unexpected shocks because event-driven interventions can be initiated and adjusted more quickly and continuously than manual responses (Calatayud et al., 2018; Rashid & Rasheed, 2025). The framework also acknowledges adoption barriers, as mid-market firms face substantial financial and time constraints when implementing digital-twin systems (Yun et al., 2024). Collectively, the hypotheses position the MBRM as a falsifiable framework in which predictive accuracy, structural resilience, information integration, and governed autonomy jointly influence logistics performance.

4. METHODOLOGY

4.1. Research Design: Sequential Mixed-Methods Approach

This study uses a sequential mixed-methods design that integrates an empirical multi-case investigation with agent-based simulation to evaluate the Model-Based Risk Management (MBRM) framework under controlled disruption conditions. The empirical phase identifies operational patterns and decision-making behaviors that inform the computational phase's parameterization and behavioral rules. Although Headley and Plano Clark (2020) primarily examined multilevel mixed-methods designs, this study uses their work to support the integration logic rather than classifying it as a multilevel study. The design is strictly sequential, combining qualitative and quantitative evidence to explain complex nonlinear phenomena. The empirical phase covers ten multinational enterprises across the sectors listed in Table 2. We used quantitative operational records and executive interviews to assess the predictive alignment, signal fidelity, operational latency, systemic resilience, and decision execution. These observations informed the second phase, which translated the empirical evidence into an agent-based simulation with 1,000 interacting agents and 2,000 simulation steps for each experimental condition. To ensure transparency and reproducibility, the model documentation follows the Overview, Design Concepts, and Details (ODD) protocol (Grimm et al., 2006, 2010), which is the field standard for agent-based modeling.



Figure 3. Two-Stage Research Methodology Design

Note. Empirical evidence informs variable operationalization, parameter ranges, and behavioral rules before controlled computational stress testing.

4.2. Case Selection, Variable Operationalization, and Calibration

Ten cases were selected based on technological maturity, organizational scale, and data accessibility. Eligibility requires at least USD \$1 billion in annual revenue, active digital transformation involving real-time data integration, predictive analytics, digital twins, or automated decision systems, and access to anonymized operational information. These criteria emphasize digitally mature enterprises and therefore limit generalizability to smaller, resource-constrained firms facing distinct adoption barriers (Yun et al., 2024).

Table 2. Profile of Selected Cases

Case	Sector	Revenue (USD)	Active Nodes	Technology Focus
A-1	Automotive	\$18B	14	Internet-of-Things (IoT) Digital Twin
R-2	Retail	\$34B	820	Dynamic Pricing Artificial Intelligence (AI)
L-3	Port Logistics	\$9B	45	Automated Routing
C-4	Chemicals	\$12B	28	Sensing Mesh / Enterprise Resource Planning (ERP)
E-5	Smart Energy	\$6B	3	Peer-to-Peer (P2P) Trading Ledger
P-6	Pharmaceuticals	\$15B	18	Cold-Chain Sensing
H-7	High-Tech Hardware	\$22B	10	Multi-Sourcing AI
F-8	Packaged Food	\$8B	52	Predictive Demand
T-9	Telecommunications	\$11B	1	Autonomous Loading
M-10	Industrial Minerals	\$5B	12	Dynamic Logistics

Note. Active nodes represent distinct operational or managerial entities that can participate in the modeled supply-chain process. Interview evidence concerning decision delays, escalation practices, intervention thresholds, and technology integration was coded and mapped to the corresponding simulation parameters and behavioral-transition rules. Quantitative records constrained plausible parameter ranges, triangulating the observed performance with the modeled behavior.

Table 3. Parameter and Variable Calibration

Variable	Symbol	Bounds	Default
Predictive Alignment (PA)	PA	0.12-0.96	Dynamic
Systemic Resilience (SR)	SR	0.85-4.82	Dynamic
Signal Fidelity (SF)	SF	0.65-0.99	0.95
Operational Latency (L)	L	0.01-86,400 s	1.2 s
Friction Coefficient (Ω)	Ω	0.05-0.85	0.15
Scaling Constant (Θ)	Θ	—	1.00
Synergy Exponent (γ)	γ	—	1.50
Volatility Sensitivity (δ)	δ	—	0.50

Note. Bounds reflect empirical observations, historical volatility patterns, and pilot simulation testing.

Operational Latency (L) is defined as: $L_i = t_{end,i} - t_{start,i}$ where $t_{start,i}$ denotes anomaly detection, and $t_{end,i}$ denotes the completion of the authorized action. The 24-h upper bound reflects legacy batch-processing cycles.

Three structural parameters—Scaling Constant (Θ), Synergy Exponent (γ), and Volatility Sensitivity (δ)—are study-specific assumptions derived from historical logistics modeling benchmarks and tested through sensitivity analysis.

4.3. Simulation and Stress-Scenario Design

The simulation was implemented in NetLogo and Python using the ODD structure. The 1,000 agents comprise 400

consumers, 100 competitors, 300 suppliers, and 200 logistics carriers. Their heterogeneous behaviors include purchasing, pricing, capacity, transportation, congestion, and responses to disruptions, which are consistent with supply chain resilience as an emergent network property (Tukamuhabwa et al., 2015; Li et al., 2020).

Table 4. Experimental Scenario Configuration

Dimension	Scenario 1	Scenario 2	Scenario 3 (MBRM)
Connectivity	Low	Moderate	High
Data Processing	Retrospective	Partially Predictive	Continuous Predictive
Digital Twins	None	Partial	Real-Time Integrated
Decision Mode	Manual	Partially Automated	Governed Automation
Risk Management	Reactive	Predictive	Predictive / Prescriptive
Execution	Manual	Partial	Autonomous / Human-Augmented
Feedback	Absent	Limited	Continuous
Security / Compliance	Basic Access	Role-Based Logging	NIST AI Risk Management Framework (AI RMF) / ISO/IEC 42001
Objective	Recovery	Responsiveness	Preventive Orchestration

Scenario 3 incorporates SHAP (Shapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) to mitigate “black box” risks. Security and compliance controls align with the NIST AI RMF and ISO/IEC 42001:2023. At simulation step 1,000, we introduced a compound disruption: a 50% reduction in supplier capacity and a 100% increase in demand volatility. We evaluated each configuration using repeated stochastic runs. We reported Predictive Alignment (PA), Systemic Resilience (SR), Operational Latency (L), and Value Orchestration Efficiency (VOE) using means, variance estimates, and 95% confidence intervals. Sensitivity analysis assesses whether comparative findings remain stable under alternative parameter values and initial conditions (Rahman et al., 2022).

5. FINDINGS

5.1. Stage 1 Empirical Results: Multi-Case Regression Analysis

The first-stage analysis examined the associations among Predictive Alignment (PA), Systemic Resilience (SR), Signal Fidelity (SF), Operational Latency (L), and Value Orchestration Efficiency (VOE) across the ten empirical cases. Because the sample comprised only ten cases ($N = 10$), a five-predictor regression model presented a substantial risk of overfitting and unstable coefficient estimates. Accordingly, the adjusted $R^2 = 0.748$ and $F = 114.28, p < .001$ are interpreted as exploratory model statistics rather than population-level evidence of causality. This interpretation aligns with established concerns that models fitted to small samples can capitalize on sample-specific characteristics and perform poorly when generalized (Babyak, 2004). Within these limitations, the results indicate positive associations between predictive-intelligence integration and the VOE. PA produced the largest standardized coefficient ($\beta = .46, p < .001$), followed by SR ($\beta = .32, p < .001$) and the $PA \times SR$ interaction ($\beta = .24, p < .001$). SF was also positively associated with VOE ($\beta = .18, p < .001$), whereas L showed a negative association ($\beta = -.29, p < .001$). These patterns are consistent with the view that resilience depends not only on analytical capability but also on the capacity to translate information into timely adaptive action (Chen et al., 2021).

Table 5. Statistical Evaluation of Value Orchestration Drivers

Independent Variable	Standardized Coefficient (B)	Standard Error	t-Statistic	p
Predictive Alignment (PA)	0.46	0.042	10.95	< .001
Systemic Resilience (SR)	0.32	0.038	8.42	< .001
PA $\times$ SR Interaction	0.24	0.031	7.74	< .001
Signal Fidelity (SF)	0.18	0.029	6.21	< .001

Operational Latency (L)	-0.29	0.035	-8.28	< .001
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Note. Adjusted $R^2 = 0.748$; $F = 114.28$, $p < .001$; $N = 10$. The coefficients represent exploratory cross-sectional associations rather than causal estimates. The positive PA coefficient offers exploratory support for Hypothesis 1, and the PA $\times$ SR interaction offers exploratory support for Hypothesis 2. The negative association between L and VOE suggests that analytical capability may have limited operational value when delays persist in anomaly detection, decision-making, and execution. These findings align with research highlighting how disruptions propagate across interconnected supply chain networks (Li et al., 2020).

5.2. Stage 2 Simulation Results: Performance Under Volatility

The second-stage agent-based simulation followed the Overview, Design concepts, and Details (ODD) protocol, which improves the completeness and reproducibility of agent-based modeling (Grimm et al., 2006, 2010). The simulation showed distinct performances across the three operating conditions. Under pre-disruption conditions, the Integrated Cognitive Platform (Scenario 3) recorded an average VOE of 83.6%, compared with 55.2% for Fragmented Digitization (Scenario 2) and 31.4% for the Legacy Descriptive configuration (Scenario 1). Following the compound disruption introduced at simulation step 1,000, Scenario 1 reached a minimum VOE of 8.2%, Scenario 2 declined to 31.8%, and Scenario 3 remained relatively stable at 76.1%. The recovery trajectories differed substantially: Scenario 1 required 840 steps, Scenario 2 required 310 steps, and Scenario 3 required 120 steps. These values indicate a substantially faster modeled recovery under the integrated configuration; however, the 120-step result was interpreted as a conditional simulation outcome rather than a universal benchmark. To ensure robustness, we evaluated the simulation through repeated stochastic runs that varied the initial conditions and the selected parameters. Therefore, the recovery time values represent scenario-level outcomes rather than deterministic predictions.

Table 6. Simulation Results Across Operating Scenarios

Performance Metric	Scenario 1: Legacy Supply Chain Management (SCM)	Scenario 2: Fragmented Digitization	Scenario 3: Integrated Cognitive Platform
Average VOE, Pre-Shock	31.4%	55.2%	83.6%
Minimum VOE, Post-Shock	8.2%	31.8%	76.1%
Recovery Time	840 steps	310 steps	120 steps
Revenue Volatility ()	14.28	6.14	1.08
Average Operational Latency	14.2 hours	3.1 hours	0.04 seconds

Note. All scenarios experienced a 50% supplier capacity reduction and 100% increase in demand volatility at step 1,000. The simulation findings provide exploratory support for Hypothesis 3, as L decreases from 14.2 h in Scenario 1 to 0.04 s in Scenario 3. They also support Hypothesis 4, with revenue volatility variance declining from 14.28 in Scenario 1 to 1.08 in Scenario 3, an approximately 92.4% reduction in the latter. We implemented interpretability diagnostics using Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) (Lundberg & Lee, 2017; Ribeiro et al., 2016). SHAP provides feature-attribution values for individual predictions, whereas LIME approximates the local model behavior. These diagnostics indicated that real-time signal weighting and multi-agent rule prioritization were influential factors in the lower latency observed in Scenario 3.

5.3. Interplay Analysis: Adaptive Capacity, Capital Efficiency, and Volatility

The interplay analysis indicates that Adaptive Capacity (ACI) shapes the relationship between working capital requirements and VOE. At a lower ACI, increases in working capital requirements are associated with larger reductions in VOE because organizations rely more heavily on physical buffers. As ACI increases, the modeled sensitivity of VOE to capital requirements declines, suggesting that digital integration complements—rather than eliminates—physical redundancy. This finding aligns with Ivanov (2023), who argued that digital intelligence complements physical supply chain structure. However, substantial infrastructure and implementation requirements may pose adoption barriers for smaller firms (Yun et al., 2024). Accordingly, the MBRM architecture shifts resilience toward dynamic visibility, scenario anticipation, and rapid reconfiguration; however, this shift is constrained by the investment required for high-fidelity digital infrastructure.

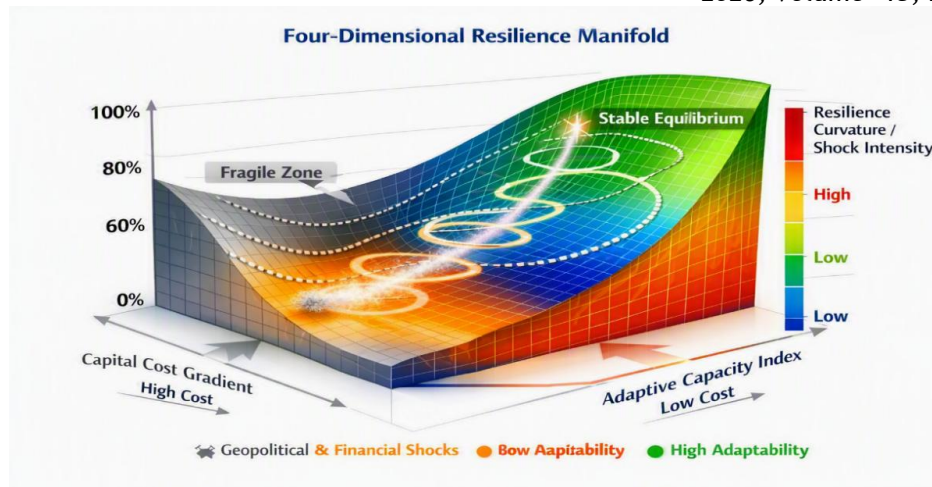


Figure 5. Value Orchestration Index as a Function of Adaptive Capacity

5.4. Qualitative Insights: Structural Roles and Strategic Stewardship

Qualitative evidence indicates that implementing the Model-Based Risk Management (MBRM) architecture depends not only on technical infrastructure but also on specialized organizational capabilities. Three recurring functional roles were identified. Data-product engineering – maintaining continuous data pipelines and digital-twin environments. Streaming-analytics translation: Converting strategic risk requirements into event-driven analytical and simulation logic. Cognitive-reliability management: monitoring model latency, data quality, execution boundaries, and system behavior. These roles suggest that autonomous logistics systems require institutional mechanisms for human oversight rather than unrestricted automation. Autonomy is treated as a governed capability that expands or contracts based on risk, uncertainty, and decision criticality. This interpretation aligns with the requirements for explainability and human oversight in consequential operational decisions (Lundberg & Lee, 2017; Ribeiro et al., 2016). Therefore, governance is positioned as an integral component of resilience, rather than an external constraint. The findings reinforce the importance of organizational learning and adaptive capabilities in sustaining resilience amid changing disruption conditions (Daghar et al., 2022; Kolt, 2025).

6. DISCUSSION

6.1. Theoretical Contributions: Redefining Logistics Risk Theory

The findings extend logistics risk theory by framing resilience as a capability that emerges from the interplay between predictive information, adaptive coordination and rapid execution. Rather than treating resilience as a static capacity, the results indicate that timely information can serve as an operational buffer, enabling organizations to reconfigure resources before disruptions propagate. This interpretation aligns with the dynamic capabilities perspective, in which sensing, seizing, and reconfiguring support sustained adaptation (Dubey et al., 2019). The significant Predictive Alignment (PA) × Systemic Resilience (SR) interaction further suggests that predictive capability delivers greater value when embedded in organizational structures capable of coordinated responses (Chen et al., 2021; Habibi et al., 2023). Accordingly, information velocity and decision-execution coherence can be treated as measurable dimensions of resilience, rather than solely technological characteristics. Interpretable artificial intelligence mechanisms, specifically Shapley Additive explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), support transparent, model-based decision processes (Feddersen & Cleophas, 2026).

6.2. Actionable Technical, Managerial, and Policy Recommendations

These findings support a staged approach to cognitive-logistics transformation. Organizations should first strengthen Internet of Things (IoT) sensing, event-driven data pipelines, and integration between operational and financial systems before expanding into digital twins and bounded autonomous execution. Automation should remain proportional to risk, with predefined intervention thresholds, human escalation, decision logging, and auditability. uch governed automation can improve response speed while maintaining accountability, particularly in contexts where autonomous decisions may have legal or operational consequences (Kolt, 2025). Digital twin-based stress testing can also help organizations evaluate the effects of nonlinear disruptions before implementing operational changes (Park et al., 2021). Therefore, these capabilities should be introduced as part of an integrated governance architecture rather than as isolated technological investments.

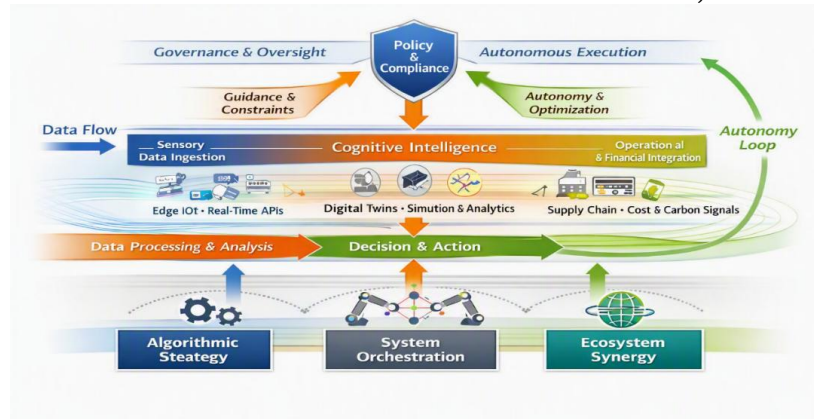


Figure 6. Strategic Blueprint for Model-Based Risk Management Deployment

6.3. Systemic Limitations and Future Research

This study had several limitations. High-fidelity digital twins require substantial data, computational resources, and organizational integration, which may limit their adoption by smaller or less digitally mature firms (Zaidi et al., 2024). Cybersecurity, privacy, interoperability, and governance remain constraints in digitally interconnected supply networks (Odimarha et al., 2024). Moreover, simulation-based findings may be sensitive to agent interactions and emergent feedback effects (Moon et al., 2018). Future research should examine federated learning, privacy-preserving computation, cross-organizational governance, and interactions among competing supply networks. Further work should also distinguish technical explainability for model validation from the managerial explainability required to establish trust, accountability, and responsible adoption (Feddersen & Cleophas, 2026).

7. CONCLUSION

7.1. Summary of Quantitative and Qualitative Insights

This study developed and evaluated a Model-Based Risk Management (MBRM) framework to strengthen predictive logistics resilience. Across empirical cases and agent-based simulations, the findings indicate that stronger Predictive Alignment (PA), Systemic Resilience (SR), and Signal Fidelity (SF) are associated with higher Value Orchestration Efficiency (VOE). A shorter decision-to-execution latency is linked to faster recovery and lower operational volatility. These results align with research emphasizing visibility, organizational learning, and the ability to anticipate and contain disruption propagation as foundational elements of supply network resilience (Chen et al., 2021; Tsolakis et al., 2021). They also reinforce the argument that resilient supply chains must balance efficiency with the capacity to absorb and adapt to persistent disruptions (Dzreke & Dzreke, 2025a). Accordingly, predictive intelligence is positioned not merely as an analytical capability but as an operational resource for anticipating, absorbing, and responding to disruptions (Nwokocha et al., 2025). The findings also highlight key implementation constraints. High-fidelity digital twin architectures can impose substantial financial, technical, and time-related demands, particularly on mid-market and resource-constrained firms (Yun et al., 2024). Human-artificial intelligence (AI) interaction may also shape their effectiveness, including algorithm aversion, in which managers reject or override algorithmic recommendations (Balakrishnan et al., 2025), and unresolved questions about accountability and liability in autonomous decision-making (Kolt, 2025).

7.2. Final Strategic Implications

The main strategic implication is that resilient logistics increasingly depend on integrating sensing, prediction, simulation, and execution within a coherent decision architecture. Rather than relying solely on physical buffers or retrospective risk reporting, organizations can combine selective redundancy with timely information, adaptive coordination, and well-governed automation to enhance resilience. This extends dynamic capability theory by emphasizing the continuous sensing of environmental change, converting information into timely decisions, and reconfiguring resources as conditions evolve (Fainshmidt et al., 2018). This also complements the evidence that digital twins and predictive analytics can improve disruption management by enhancing visibility, scenario evaluation, and coordinated response (Liu et al., 2026). Emerging work on self-optimizing supply ecosystems further highlights the potential of predictive intelligence and adaptive optimization to support continuous resource reconfiguration (Dzreke et al., 2026d). However, the MBRM should not be viewed as a universal substitute for inventory buffers, supplier diversification, physical capacity, or other established resilience investments. Its value depends on data quality, organizational capabilities, governance arrangements, and effective management of the human-AI interface. Therefore, accountability and regulatory requirements are essential for responsible implementation. The study's central contribution is the integration of predictive alignment and systemic resilience into a measurable decision

framework that explains how information can be converted into timely, value-preserving actions under conditions of logistics uncertainty.

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