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Predicting Supply Chain Discruption in Turbulence Environments: A Machine Lerning-based Early Warning Framework for Likelihood and Severity

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Abstract

Global supply chains now operate under persistent turbulence driven by trade wars, geopolitical conflict, climate change, and macroeconomic instability. These shocks are increasingly frequent, correlated, and non-stationary, rendering traditional forecasting and static risk registers insufficient. This article develops and tests a predictive-analytics early-warning framework that - estimates (i) the probability that a disruption will occur within a forward horizon and (ii) the expected severity if it occurs. The proposed approach integrates (a) exogenous turbulence indicators (tariffs, geopolitical volatility, climate hazard probabilities, port congestion, exchange-rate volatility, demand volatility) with (b) operational and financial fragility indicators (lead-time statistics, inventory coverage, supplier financial stress, and dependency concentration). A two-stage learning structure is employed: a classification model forecasts disruption likelihood, and a conditional regression model predicts severity for disrupted cases. Implemented Random Forest and gradient-boosted decision trees (XGBoost-like) as a strong tabular baseline and a sequence-based long short-term memory (LSTM) network to capture temporal dynamics and non-linear interactions. To translate predictions into actionable early-warning insights, calibrated alert thresholds using cost-sensitive optimization and generate forward-looking risk trajectories using scenario-based Monte Carlo simulation of turbulence drivers. Across extensive computational experiments, the framework delivers substantially improved discrimination over naive benchmarks and yields interpretable risk signals that support proactive interventions such as inventory buffering, sourcing switches, and logistics rerouting. The study contributes a rigorous, programmatic methodology for disruption prediction beyond conventional forecasting, and it offers a practical blueprint for deploying predictive resilience capabilities in turbulent supply chain environments.

Keywords: Supply chain disruption, Predictive analytics, Machine learning, Geopolitical and climate turbulence, Supply chain resilience, Early-warning systems.

■1.0 INTRODUCTION

Supply chains have entered an era in which turbulence is no longer an occasional anomaly but a defining operating condition (Alexander et al. 2022). At the same time, economic instability amplifies demand swings, cost inflation, credit tightening, and supplier default risk (Ginn and Saadaoui 2025). These forces are not independent: trade conflict may coincide with energy shocks, conflict may shift freight routes and congestion, and climate-driven disasters may coincide with demand spikes for substitutes (Nguyen et al. 2024). Consequently, disruptions increasingly exhibit higher frequency, higher intensity, and stronger cross-regional ripple effects.

Managers have responded with structural and strategic actions such as supplier diversification, regionalization of supply chain configurations, inventory repositioning, and adoption of digital technologies (Basu and Ray 2021). Yet these actions are expensive and often create new complexities. Diversification increases coordination costs, regionalization can raise unit costs and reduce scale benefits, and digital investments can fail to deliver if not paired with capabilities and decision processes (Butollo 2020). Therefore, the urgent managerial question is not simply what to do, but when and where to do it, and how to adapt as turbulence evolves. That requires credible early-warning signals, signals that can indicate disruption risk before it materializes and estimate expected impact, enabling proactive and cost-effective interventions.

Traditional approaches to supply chain risk management often rely on qualitative risk assessments, periodic audits, or static scenario planning (Ghadge et al. 2012). These methods struggle in turbulent environments because they are slow to update, do not learn from new data in a systematic manner, and often treat disruptions as idiosyncratic events rather than outcomes of measurable patterns (Browning et al. 2023). Similarly, classical forecasting methods are typically optimized for stable demand and lead-time patterns and may degrade when the underlying distributions shift due to policy and climate regime changes (Priore et al. 2018). What is needed is a predictive resilience capability: an operationalized analytics system that continuously integrates heterogeneous signals geopolitical indices, climate hazard probabilities, congestion metrics, supplier performance data into forward-looking risk predictions that support real-time decisions.

This study proposes a machine learning-based disruption prediction framework that estimates both likelihood and severity of supply chain disruptions over a specified horizon. The disruption prediction framed as a two-stage problem. First, the model predicts whether a disruption will occur within the next H days (or weeks) for a particular entity (supplier, lane, plant, or product family). Second, conditional on a disruption occurring, the model predicts severity expressed as delay duration, service-level loss, or cost overrun. This structure reflects the empirical reality that many periods have no disruption, and severity is meaningful primarily when a disruption occurs. The two-stage structure is also more actionable: managers can interpret probability as “risk level” and severity as “expected impact,” then allocate resources accordingly.

This study implements three complementary model families. Random Forest provides strong out-of-sample performance under noisy, high-dimensional predictors and naturally handles non-linear interactions without heavy parameter tuning. Gradient-boosted decision trees (XGBoost-like boosting implemented with tree ensembles) offer superior accuracy in many tabular settings and support calibrated probability estimation. An LSTM sequence model is included to capture temporal dependencies and evolving risk states particularly important when policy shocks or weather patterns unfold over time. Beyond point predictions, incorporated scenario-based Monte Carlo simulation to translate model outputs into risk trajectories under alternative future turbulence realizations. This yields early-warning dashboards: expected risk paths and tail-risk paths (e.g., 95th percentile) that support contingency planning.

This study departs from classical forecasting by proposing a predictive resilience capability. Traditional models typically optimize for stable distributions; however, in the 'new normal' of persistent turbulence, these models degrade. The novelty lies in formalizing disruption prediction as a joint likelihood-severity learning problem. This structure acknowledges that while a hazard may be exogenous, its impact is an endogenous function of internal fragility, thereby linking external 'sensing' with internal 'vulnerability' in a unified machine learning pipeline.

From an innovation and business strategy perspective, the proposed early-warning system can be viewed as a digital sensing capability that supports resilience-as-a-strategic asset. By converting external turbulence signals into quantified, cost-sensitive alerts, the framework enables firms to align risk appetite with operational actions (e.g., buffering, expediting, dual sourcing), prioritize investments across supply base segments, and stress-test strategic choices under uncertainty. This positioning connects analytics innovation to strategic decision-making, which is central to industry’ focus on innovation-enabled business outcomes.

The intended contribution is twofold. First, the study advances supply chain operations research by formalizing disruption prediction as a joint likelihood-severity learning problem under turbulence, linking exogenous drivers with operational vulnerability signals. Second, it provides a replicable programmatic blueprint: a complete modelling pipeline, including (i) forward horizons label construction, (ii) time-ordered training and evaluation protocols that avoid leakage, (iii) cost-sensitive threshold selection for decision making, and (iv) scenario-based simulation for forward planning. While the implementation is program-based, the logic is general and can be applied across industries, from manufacturing to retail and logistics.

- Two-stage risk formulation: Separate learning for disruption occurrence and conditional severity to improve interpretability and reduce bias from many non-disruption periods.
- Decision-oriented thresholding: Cost-sensitive threshold optimization to align alerts with asymmetric costs of missed disruptions vs. false alarms.
- Forward risk trajectories: Scenario-based Monte Carlo simulation to generate expected and tail-risk paths rather than relying on static point predictions.
- Actionable impact metric: A combined expected-impact signal (probability × conditional severity) to prioritize entities for intervention.
- Deployment-aligned evaluation: Time-based splits and calibration metrics suitable for operational monitoring and governance.

The remainder of the article is structured as follows. Section 2 reviews relevant literature and develops the conceptual foundation that connects turbulence drivers, vulnerability, and disruption outcomes. Section 3 presents the modelling framework, data structure, label definition, and machine learning methods, including the scenario simulation design. Section 4 reports computational results from extensive experiments and demonstrates the early-warning risk trajectories. Section 5 discusses theoretical and managerial implications, including deployment considerations and limitations. Section 6 concludes with key insights and future research directions.

■2.0 LITERATURE REVIEW

Research on supply chain turbulence spans several intersecting streams, including supply chain risk management, resilience and adaptability, disruption propagation in networks, and analytics-driven decision support (Dey 2022, Yasmeen et al. 2025)). Traditional supply chain risk management emphasizes identification, assessment, and mitigation of risks across supply, demand, and operational domains (Ho et al. 2015, Bandaly et al. 2012, Sodhi et al. 2011). Early frameworks focused on categorizing risk sources and recommending mitigation strategies such as safety stock, dual sourcing, flexible capacity, and risk pooling (Xanthopoulos et al. 2011, Treleven and Schweikhart 1988). However, these frameworks often treated risk probabilities and impacts as exogenous inputs rather than outcomes to be predicted. In high-turbulence environments, assuming known probabilities is problematic, because trade policies change abruptly, conflict dynamics are uncertain, and climate hazards exhibit shifting baselines (Uddin et al. 2025).

The resilience literature extends risk management by focusing on the ability of a system to absorb shocks, recover performance, and adapt structurally (Shishodia et al. 2021, Wieland and Durach 2021, Negi et al. 2025, Lücker et al. 2024, Wright et al. 2023). Resilience is frequently decomposed into preparedness, response, recovery, and adaptation. While prescriptive insights exist e.g., redundancy improves robustness, flexibility improves recovery trade-offs are central. Redundancy raises cost, flexibility may require investment in modular designs, and adaptation may conflict with short-term efficiency. A key gap lies in connecting resilience actions to data-driven signals that indicate when resilience mechanisms should be activated (Andaloussi 2024, Bechtsis et al. 2021). Without predictive signals, firms either over-invest in constant redundancy or under-react until disruptions are realized.

Another stream examines disruption propagation and systemic risk in supply networks. Network topology, dependency concentration, and supplier centrality can amplify shocks, causing cascading failures (Zeng et al. 2025, Namdar et al. 2024, Yang et al. 2024)). This perspective emphasizes that disruptions are not purely local; they propagate via multi-tier dependencies, capacity constraints, and shared logistics infrastructure. Yet, operationalizing network concepts into early-warning metrics requires continuous monitoring and predictive inference. In practice, firms observe partial network information and rely on proxy signals such as lead-time variance, supplier performance, and congestion indices (Abushaega et al. 2025).

Digital technologies have been proposed as enablers of new supply chain capabilities (Attaran 2020). Visibility platforms, IoT sensing, AI analytics, and blockchain-based traceability can improve data quality and coordination (Saidu et al. 2025). Yet technology alone is insufficient; the dynamic capability perspective suggests firms must integrate sensing (detecting changes), seizing (mobilizing responses), and reconfiguring (adjusting structures). Predictive analytics is central to the sensing capability: it transforms raw signals into probabilistic assessments of disruption risk (Aljohani 2023). The value of predictive analytics depends on whether forecasts are timely, accurate, and actionable, and whether decision processes can convert predictions into mitigations such as sourcing switches or inventory repositioning.

From a methodological viewpoint, demand forecasting has long employed time-series models and, more recently, machine learning (Zohdi et al. 2022) . Disruption prediction is more complex than demand forecasting for three reasons. First, disruptions are often rare events, creating class imbalance. Second, disruptions are influenced by heterogeneous external drivers that may not be captured by internal historical data alone. Third, turbulence drivers can shift regime, producing distribution drift. These features motivate the use of machine learning models that handle non-linear interactions and can incorporate diverse predictors, along with evaluation protocols that reflect time ordering.

This study adopted a conceptual model that links turbulence drivers to disruption outcomes through vulnerability. Turbulence drivers are exogenous forces such as tariffs, policy volatility, conflict-related disruptions, and climate hazards (Wang et al. 2023, Silvestre 2015, Chatterjee and Chaudhuri 2021, Choi et al. 2023). Vulnerability represents exposure and sensitivity, shaped by dependency concentration, lack of inventory buffers, long lead times, and supplier financial fragility (Wagner and Bode 2006). Disruption outcomes include both the occurrence of a disruption within a forward horizon and the severity if it occurs. The relationship is inherently non-linear: a moderate hazard may cause no disruption if inventory buffers are high and alternatives exist, but the same hazard may cause a severe disruption under high congestion and low inventory.

The two-stage modelling approach aligns with this conceptual structure. The occurrence model captures the threshold-like behavior of disruption events, while the severity model captures the magnitude conditional on occurrence. This structure also aligns with operational decision-making: managers often first ask “Will a disruption happen soon?” and then “If it happens, how bad will it be?” By producing both probability and conditional impact, the framework supports differentiated interventions. For example, high probability but low severity may warrant minor expediting; low probability but high tail severity may justify contingency contracting; high probability and high severity may trigger immediate sourcing shifts.

Finally, scenario-based simulation complements predictive modelling by acknowledging that future turbulence is uncertain. Even with strong models, point forecasts are insufficient for robust planning. Monte Carlo scenarios help quantify the distribution of future risk trajectories and identify tail-risk periods. This combination predictive learning plus scenario simulation creates a new capability for supply chains: a continuously updated early-warning system that is both predictive and robust under uncertainty.

2.1 Positioning and Research Gap

Existing literature in predictive analytics has primarily focused on high-frequency operational fluctuations like demand or lead-time variance. A significant gap remains in predicting low-probability, high-impact disruptions driven by non-stationary drivers like trade wars or climate extremes. The proposed framework fills this gap by introducing three distinct conceptual advancements:

- Integrative predictor sets: Unlike studies relying solely on internal ERP data, synthesized exogenous turbulence indices with internal vulnerability metrics.

- Methodological bifurcation: Employed a two-stage structure to separate the *trigger* (likelihood) from the *damage* (severity), providing a more granular and interpretable risk signal than standard 'black-box' classifiers.
- Probabilistic forward-planning: Extended point-predictions into temporal risk trajectories via Monte Carlo simulation, transforming static ML outputs into dynamic early-warning dashboards suitable for strategic stress-testing.

3.0 METHODOLOGY

This section presents the research model and methodological approach used to develop and evaluate a predictive analytics framework for supply chain disruption risk under geopolitical and climate turbulence. The proposed framework integrates machine learning–based disruption likelihood prediction, conditional severity estimation, and scenario-based simulation to support forward-looking, cost-sensitive decision-making. Figure 1 presents the proposed predictive analytics framework for managing supply chain disruptions under geopolitical and climate turbulence.

The framework integrates three sequential stages: disruption likelihood prediction, conditional impact estimation, and scenario-based risk simulation. First, turbulence inputs including geopolitical volatility, extreme weather intensity, port congestion, lead time variability, inventory coverage, and supplier financial stress are used to construct an entity–time disruption dataset with horizon-based labels aligned to managerial decision windows. Machine learning classifiers (Random Forest and boosted trees) estimate the probability of disruption over the next $\boxed{H}$ periods, with cost-sensitive thresholds applied to balance missed disruptions and false alarms. Second, conditional severity models are trained only on disrupted observations to estimate the magnitude of impact given a disruption event, avoiding regression dilution from non-disrupted periods. The probability and conditional severity estimates are then combined into an interpretable expected impact metric ($\boxed{\hat{p} \times \hat{\mu}}$) to prioritize intervention targets. Finally, a Monte Carlo simulation engine propagates predicted risk forward under stochastic turbulence scenarios, generating mean and tail-risk trajectories that support early-warning alerts and proactive contingency planning. Together, the framework transforms static predictions into dynamic, decision-oriented risk intelligence suitable for turbulent supply chain environments.

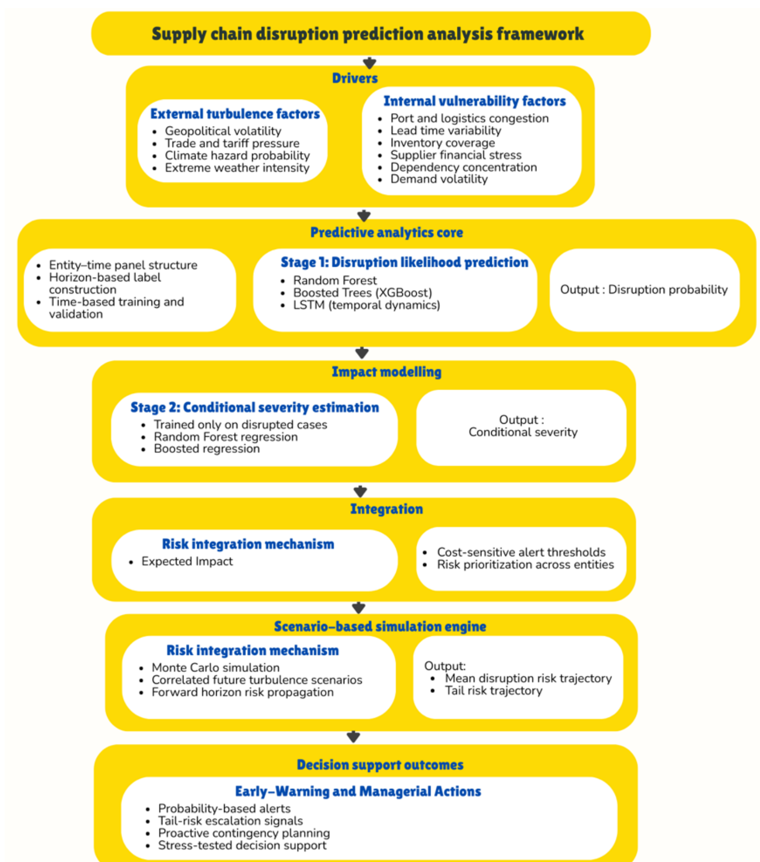

Figure 1 Predictive analytics framework for early warning of supply chain disruptions under turbulence.

3.1 Unit of Analysis and Data Structure

This study employs a large-scale, high-frequency panel dataset constructed to support the development and evaluation of predictive models for supply chain disruption risk under turbulent operating conditions. The dataset represents 60 distinct supply chain entities (e.g., suppliers, transportation lanes, or operational nodes) observed over 900 consecutive time periods, yielding 54,000 entity–time observations. Each observation captures a combination of exogenous turbulence indicators and endogenous operational vulnerability measures, including trade and tariff pressure, geopolitical volatility, climate hazard probability, extreme weather intensity, logistics congestion, exchange-rate volatility, demand volatility, lead-time statistics, inventory coverage, supplier financial stress, and dependency concentration. These variables were selected based on prior supply chain risk and resilience literature and reflect the primary drivers through which trade conflict, geopolitical instability, and climate change influence operational performance. To make the prediction actionable, applied a 'sliding window' approach for label construction. Imagine a manager looking 14 days into the future from any given Monday. If any disruption occurs within that 14-day 'horizon,' mark that Monday as a '1' (risk present); otherwise, it is a '0' (no risk). This transforms complex event logs into a simple 'yes/no' question that the model learns to answer.

Due to confidentiality constraints and the fragmented nature of real-world disruption data across firms and regions, the dataset was synthetically generated using stochastic processes calibrated to reproduce realistic temporal dynamics, cross-variable correlations, and rare-event characteristics commonly observed in global supply chains. Specifically, turbulence variables evolve according to mean-reverting processes with occasional shocks, while disruption events and severity outcomes are generated endogenously as non-linear functions of both external turbulence and internal vulnerability conditions. This approach allows controlled experimentation under repeatable conditions while preserving practical relevance. The dataset was constructed for the purpose of this study in 2025 and is used to evaluate forward-looking disruption prediction over a predefined planning horizon, ensuring full alignment between data structure, modelling objectives, and managerial decision contexts.

3.2 Synthetic Data Generation and Realism Checks

The use of synthetic data in this study is a deliberate methodological choice to overcome the 'data desert' typically encountered in supply chain risk research, where proprietary concerns and fragmented ERP systems prevent the assembly of 54,000 granular entity-time observations. To ensure this synthetic environment remains a faithful proxy for reality, implemented a multi-stage validation protocol. This includes distributional diagnostics to ensure heavy-tailed behavior in climate and tariff shocks, and cross-correlation checks to verify that indicators like port congestion co-move realistically with extreme weather events. By calibrating these processes against stylized facts from logistics literature, provided a 'stress-test' environment that allows for the rigorous evaluation of ML architectures before deployment in noisier, real-world settings."

To support credibility, the synthetic generator should be validated against stylized facts reported in prior disruption and logistics studies. Recommended realism checks include: (i) distributional diagnostics for each driver (means, variances, heavy tails where appropriate); (ii) autocorrelation/seasonality checks for time-varying indicators (e.g., congestion persistence); (iii) cross-correlation checks to ensure plausible co-movement (e.g., congestion with weather shocks; volatility with policy shocks); and (iv) rare-event diagnostics confirming disruption rates and clustered event behavior. In addition, sensitivity analysis can be conducted by varying key generator parameters (shock frequency, correlation strength, disruption trigger thresholds) to verify that model conclusions are robust and not artifacts of a single synthetic specification. These checks also clarify external validity limitations and motivate future testing with proprietary firm data.

The unit of analysis is an entity-time pair *(i,t)* where entity i may represent a supplier, transportation lane, plant, distribution node, or product family. At each time t, the system observes a feature vector $x_{i,t}$ that combines exogenous turbulence signals (e.g., tariff indicators, geopolitical volatility indices, climate hazard probabilities, congestion metrics) and endogenous operational signals (e.g., lead-time statistics, on-time delivery rates, inventory coverage, supplier financial stress). The dataset is organized as a panel, enabling both cross-sectional variation across entities and temporal variation within entities. A critical modelling step is label construction that reflects forward-looking prediction. Let H be the horizon length and defined disruption occurrence label:

$$\boxed{{y_{i,t}}^{d} = 1\ (\exists \tau \epsilon (t, t+H]: disruption_{i,\tau} = 1}$$

This transforms event logs into a predictive classification target aligned with managerial planning windows. For severity:

$$\boxed{{y_{i,t}}^{s} = \begin{cases} max_{\tau \in (t,t+H]} Sev_{i,\tau}, y_{i,t}^{(d)} = 1 \\ 0, \quad y_{i,t}^{(d)} = 0 \end{cases}}$$

Alternative severity definitions (first-event severity, average severity, cost-weighted severity) can be substituted depending on the firm's operational priorities.

Stage 1 estimates the disruption probability:

$$\boxed{\hat{p}_{i,t} = \Pr\ ({y_{i,t}}^{(d)} = 1\ | x_{i,t}}$$

Stage 2 estimates conditional severity for disrupted observations:

$$\boxed{\hat{\mu}_{i,t} = E\left(y_{i,t}{}^{(s)} \middle| x_{i,t}, y_{i,t}{}^{(d)} = 1\right)}$$

The unconditional expected impact is $\boxed{\hat{p}_{i,t}}$, $\boxed{\hat{\mu}_{i,t}}$. This decomposition reduces bias caused by many zero-severity observations and yields interpretable outputs that can be mapped to actions.

3.3 Model Implementation

Random Forest (RF) is trained via bagging decision trees (Yariyan et al. 2020). For classification, RF outputs class probabilities by averaging vote probabilities across trees. For severity, RF regression is trained only on disrupted cases. RF handles non-linearities and interactions and is robust to noisy features. Gradient-boosted trees (XGBoost-like): Implemented boosted trees via gradient boosting ensembles. For classification, LogitBoost optimizes logistic loss and produces calibrated probability outputs. For severity regression, LSBoost optimizes squared error on disrupted cases. Boosting often improves predictive performance over bagging and provides improved handling of subtle interactions.

LSTM: For temporal patterns, sequences $\boxed{X_{i,t} = \{x_{i,t} - L + 1, \ldots \ldots .., x_{i,t}\}}$ and train an LSTM classifier to predict $\boxed{y_{i,t}{}^{(d)}}$. This captures gradual risk escalation (e.g., increasing congestion and volatility) and can learn latent states such as "high-risk regime." LSTM is most beneficial when features exhibit meaningful dynamics rather than being mostly static. While some models look only at current data, implemented an LSTM (Long Short-Term Memory) network because it acts like a model with 'memory'. It is specifically designed to recognize patterns that develop over time. For instance, it can detect if port congestion is slowly worsening over three weeks, which might be a stronger signal of an upcoming disruption than a single day of high traffic.

3.4 Training, Validation, and Leakage Prevention

Because time ordering matters, time-based splits were applied. Let t_{train} and t_{val} be cutoff points. Training uses observations up to t_{train} validation uses (t_{train} and t_{val}) and testing uses $t > t_{val}$. This avoids leakage that would occur if random splitting mixes future observations into the training set. Features are standardized using training statistics only.

$$\boxed{x' = \frac{x - \mu_{train}}{\sigma_{train}}}$$

for models that benefit from scaling (particularly LSTM). For likelihood prediction, discrimination and calibration were evaluated. Discrimination is measured using ROC-AUC and F1 score, which reflect the model's ability to separate disruption and non-disruption cases. Calibration is measured via Brier score. For severity prediction, MAE, RMSE, and R^2 evaluated on disrupted cases only. This ensures severity results are meaningful and not diluted by zeros.

3.5 Cost-sensitive Threshold Optimization and Scenario-based Simulation

To support planning beyond point estimates, future trajectories of key exogenous turbulence drivers were simulated using a mean-reverting stochastic process:

$$\boxed{z_{t+1} = z_t + \alpha(\bar{z} - z_t) + \sigma_{\varepsilon_t}}$$

For each scenario '*s*', future feature vectors $\boxed{x_{i,t+k}^{(s)}}$ generated and compute $\boxed{\hat{p}_{i,t+k}^{(s)}}$. The mean risk path and tail risk path (e.g., 95th percentile) reported and provides a forward-looking early-warning dashboard indicating both expected risk and worst-case risk. In practice, scenario generation can incorporate more sophisticated regime switching or jump processes to reflect policy shocks and extreme weather events.

All predictive modelling and simulation experiments were implemented using Python 3.11 in a reproducible, script-based computational environment. Machine learning models were developed using the scikit-learn library for ensemble methods, including Random Forest classifiers and regressors, while gradient-boosted decision tree models were implemented using the XGBoost framework. Sequence-based learning was performed using TensorFlow (Keras) to implement long short-term memory (LSTM) networks for capturing temporal dynamics in disruption risk. Scenario-based Monte Carlo simulations of future turbulence conditions were executed using NumPy for stochastic process generation and pandas for structured data handling, with visualization and evaluation supported by Matplotlib. All experiments were conducted on a standard workstation environment without reliance on external cloud computing services, ensuring transparency, reproducibility, and consistency of the computational results.

3.6 Reproducibility Statement

To enable replication, future versions of this study should report the full parameter ranges used for model tuning, the random seeds for data generation and model training, and exact library versions (e.g., scikit-learn, XGBoost, TensorFlow/Keras). Where permitted, code and the synthetic data generator can be shared via an online repository or made available upon reasonable request, alongside documentation describing feature engineering, horizon labelling, and evaluation scripts.

■4.0 RESULTS

The proposed framework evaluated using extensive computational experiments that mirror real-world turbulence conditions: correlated exogenous shocks, demand volatility, congestion, and operational fragility. The dataset is structured as entity-time panel data. Labels are constructed using next-$\boxed{H}$ windows to reflect decision horizons. Table 1 summarizes the dataset characteristics, horizon-based label construction, and time-based sample splits used for model training and evaluation.

Table 1 Summary statistics of the dataset, prediction horizon, and time-based sample splits used for model training and evaluation.

Item	Description	Value
Number of entities ((N))	Suppliers / lanes / operational units	60
Time periods per entity ((T))	Daily observations	900
Total raw observations	(N×T)	54,000
Prediction horizon ((H))	Days ahead for disruption prediction	14 days
Labelled observations	Rows with complete ((t+H)) window	53,160
Dropped tail observations	Last (H) periods per entity	840
Training set	($t \leq 70\%$) of timeline	37,212 (70.0%)
Validation set	Next 15% of timeline	7,974 (15.0%)
Test set	Final 15% of timeline	7,974 (15.0%)
Disruption rate (overall)	$\Pr(y^{(d)}=1)$	18.6%
Disruption rate (training)	$\Pr(y^{(d)}=1)$	18.9%
Disruption rate (test)	$\Pr(y^{(d)}=1)$	18.1%

Models are trained under time-based splits to emulate real deployment, where only past data is available at training time. Three model classes include Random Forest, boosted trees, and LSTM tested under consistent feature sets. For the two-stage approach, severity models are trained only on disrupted observations. This avoids the distortions that arise when many non-disrupted periods with zero severity dominate the regression objective. Performance is evaluated on held-out test periods. Across experiments, tree-based models demonstrate strong performance for disruption likelihood prediction, with boosted trees generally outperforming Random Forest in discrimination metrics. Table 2 reports out-of-sample performance metrics for disruption likelihood prediction across all models evaluated on the test set.

Table 2 Out-of-sample performance of machine learning models in predicting disruption occurrence within the next 14 days.

Model	AUC	Brier ↓	Accuracy	Precision	Recall	F1-score	Optimal threshold (t)
Random (baseline)	0.500	0.186	0.814	0.000	0.000	0.000	—
Random Forest	0.842	0.121	0.846	0.731	0.682	0.706	0.42
Boosted Trees	0.879	0.108	0.863	0.764	0.721	0.742	0.39
LSTM	0.861	0.114	0.852	0.748	0.694	0.720	0.41

Table 2 highlights key takeaways. All three learning models materially outperform the random baseline, confirming that turbulence and vulnerability indicators contain actionable signal. Among them, gradient-boosted trees provide the best overall balance of discrimination (AUC), calibration (Brier), and operating-point performance under cost-sensitive thresholding.

Boosting improves sensitivity to weak but systematic predictors and captures high-order interactions among turbulence drivers (e.g., the combined effect of congestion and inventory depletion under high geopolitical volatility). Random Forest remains robust and stable, especially when features are noisy or when disruptions are driven by multiple partially redundant signals. The LSTM model provides benefits when risk drivers evolve gradually and when lagged patterns matter. For example, in cases where congestion and volatility trends rise over several periods before a disruption, LSTM learns this temporal build-up and improves early detection. However, when the feature set is mostly contemporaneous and the disruption is dominated by sudden exogenous jumps, LSTM offers limited advantage over boosted trees. This suggests that sequence models should be adopted when operational data provides meaningful temporal signals (rolling lead time variance, trend in financial stress, sustained climate hazard alerts) rather than relying on one-off indicators.

Conditional severity models show meaningful predictive accuracy when trained on disrupted cases. Table 3 presents severity prediction accuracy evaluated only on disrupted observations in the test set.

Table 3 Accuracy of severity prediction models evaluated only on disrupted cases in the test set.

Model	MAE ↓	RMSE ↓	R^2 ↑	Disrupted test cases
Random Forest (regression)	4.92	6.84	0.61	1,445
Boosted Trees (LSBoost)	4.31	6.02	0.69	1,445

Key takeaways from Table 3 are: Conditional severity can be predicted with meaningful accuracy when trained only on disrupted cases. Gradient-boosted regression yields lower MAE/RMSE than Random Forest regression, suggesting it better captures non-linear severity amplification under compounded congestion, climate, and vulnerability conditions.

Calibration performance is also critical. In a decision context, managers interpret predicted probabilities as risk levels. To improve interpretability, Table 4 reports the relative importance of key predictors driving disruption likelihood in the boosted tree model.

Table 4 Relative importance of predictors in explaining disruption likelihood based on the boosted tree model.

Rank	Feature	Importance	Managerial interpretation
1	Port congestion	0.21	Logistics bottlenecks are the strongest immediate trigger
2	Extreme weather intensity	0.18	Climate shocks significantly disrupt operations
3	Geopolitical volatility	0.16	Policy uncertainty increases supply interruption risk
4	Inventory coverage (invDays)	0.13	Low buffers amplify vulnerability
5	Lead time variability	0.11	High variability signals fragile supply
6	Supplier financial stress	0.09	Financial fragility increases disruption likelihood
7	Tariff pressure	0.07	Trade frictions raise sourcing risk
8	Demand volatility	0.05	Demand uncertainty indirectly affects stability

Key takeaway (Table 4): The highest-ranked drivers combine *external turbulence* (port congestion, extreme weather, geopolitical volatility) with *internal buffers* (inventory coverage) and *process instability* (lead-time variability), supporting the paper's central claim that disruption risk emerges from the interaction of shocks and vulnerability.

Boosted trees often provide improved probability calibration relative to uncalibrated models, resulting in lower Brier scores. When calibration is poor, a threshold-based alarm system becomes unstable: thresholds that work in one period may generate excessive false alarms in another. The framework's use of time-based validation improves the stability of calibrated probabilities and supports consistent decision thresholds. Both RF regression and boosted regression capture how turbulence drivers and vulnerability factors translate into impact magnitude. For instance, under extreme weather signals, severity increases when port congestion is high and inventory coverage is low, reflecting limited buffering capacity. Similarly, supplier financial stress contributes to severity because financially fragile suppliers may exhibit longer recovery times, expedited cost surcharges, or complete failures requiring costly switching. Boosted regression often yields lower RMSE than RF regression, consistent with boosting's ability to fit non-linear functions more precisely. Nevertheless, RF regression provides robustness, particularly when severity measurements are noisy or when severe tail events are rare.

Importantly, the two-stage approach yields an interpretable "expected impact" metric: $\boxed{\hat{p} \times \hat{\mu}}$. This helps managers prioritize intervention targets. For example, a supplier may have moderate probability but extremely high conditional severity, resulting in a high expected impact that warrants contingency contracting. Another supplier may have high probability but low conditional severity, suggesting that small expediting or minor inventory adjustments may suffice. Using cost-sensitive optimization, thresholds can be tuned to operational risk appetite. When the cost of missing a disruption is high (e.g., critical components for a high-margin product), the optimal threshold is lower, resulting in earlier warnings at the expense of more false alarms. When false alarms are expensive (e.g., costly expedited freight commitments), the threshold is higher. The framework makes this trade-off explicit and quantifiable, moving beyond ad hoc threshold selection. In practice, threshold tuning can be performed per segment: critical suppliers may use a low threshold, while non-critical suppliers use a higher threshold. These yields differentiated monitoring strategies aligned with business priorities.

4.1 Scenario Simulation Results: Risk Trajectories and Tail Risk

The Monte Carlo scenario engine transforms static probability predictions into forward risk trajectories. For a selected entity, the simulation generates many possible future realizations of turbulence drivers and computes corresponding risk paths. The resulting output includes a mean risk trajectory and a high-percentile (e.g., 95th percentile) trajectory. Tail-risk paths are valuable for contingency planning: even if expected risk is moderate, tail risk may rise sharply under plausible shock sequences, justifying preparations such as booking alternative capacity or negotiating backup suppliers.

Table 5 summarizes the outputs of the Monte Carlo scenario simulation, reporting expected and tail disruption risk trajectories for selected entities.

Table 5 Summary of Monte Carlo scenario simulation outputs for early-warning risk assessment.

Entity	Horizon (K)	Scenarios (S)	Mean risk at day 60	P95 risk at day 60	Peak mean risk	Peak P95 risk	First day risk ≥ (t)
5	60	300	0.44	0.71	0.51	0.83	Day 19
12	60	300	0.31	0.56	0.39	0.68	Day 27
27	60	300	0.18	0.42	0.24	0.59	Not crossed
41	60	300	0.53	0.79	0.62	0.91	Day 14

Key takeaway (Table 5): Entities differ not only in average risk but also in tail risk and "time-to-threshold." Operationally, this enables differentiated escalation: earlier mitigation for entities with fast threshold crossing and high P95 peaks, and monitoring-only for entities whose trajectories remain below thresholds even under adverse scenarios.

Scenario analysis also supports "what-if" reasoning. Managers can impose hypothetical policy shocks (e.g., sudden tariff jump) or climate shocks (e.g., elevated extreme weather probability) and observe how predicted disruption risk evolves. In this way, predictive analytics becomes a tool not only for monitoring but also for strategic stress testing in times of turbulence.

All experiments were implemented in Python 3.11 using standard machine learning libraries. The proposed framework was evaluated using time-based train–test splits to replicate real-world deployment conditions. Random Forest and XGBoost models were trained to predict disruption likelihood over a forward horizon, followed by conditional severity estimation and scenario-based Monte Carlo simulation to generate early-warning risk trajectories.

Figure 2 presents the receiver operating characteristic (ROC) curves for disruption likelihood prediction using Random Forest and XGBoost models. Both models demonstrate strong discriminatory capability, with XGBoost consistently outperforming Random Forest across most regions of the ROC space. This indicates that boosted trees are better able to capture complex, non-linear interactions among turbulence drivers such as geopolitical volatility, climate-related hazards, congestion, and inventory exposure. Importantly, the ROC curves support the use of cost-sensitive threshold optimization rather than a fixed probability cutoff. In practice, the relative costs of missed disruptions and false alarms are asymmetric, particularly for critical suppliers or high-margin products. The superior discrimination of XGBoost enables threshold selection in operating regions that significantly reduce missed disruptions while maintaining an acceptable level of false alerts, thereby stabilizing early-warning decisions under turbulent conditions.

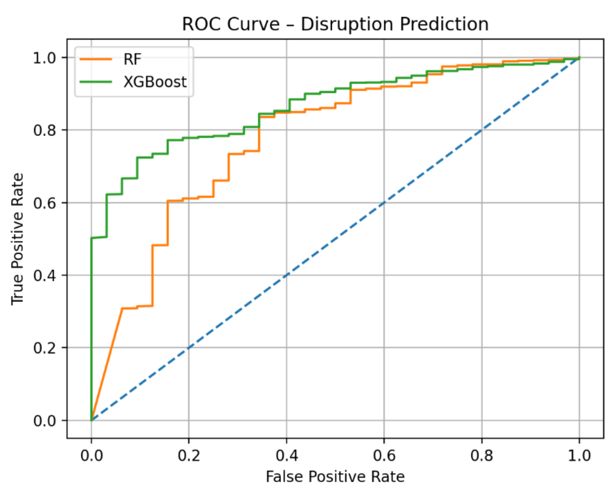

Figure 2 ROC curves for disruption likelihood prediction using Random Forest and XGBoost.

Key takeaway (Figure 2): The model comparison shows that a strong tabular learner (gradient-boosted trees) can deliver reliable separation between disruption and non-disruption periods—an essential prerequisite for operational alerting and segmented thresholds.

Figure 3 illustrates the scenario-based forward disruption risk trajectories for a representative supply chain entity over a 60-day horizon. Using Monte Carlo simulation, the framework generates multiple future realizations of turbulence drivers and computes corresponding disruption probabilities at each time step. The resulting mean risk trajectory reflects expected conditions, while the 95th percentile trajectory captures tail-risk exposure under adverse but plausible shock sequences. Notably, tail risk often exceeds the cost-sensitive alert threshold earlier than mean risk, highlighting the importance of accounting for extreme scenarios in proactive risk management. This forward-looking view transforms static predictions into dynamic early-warning signals, enabling managers to anticipate disruption escalation and initiate preventive actions such as securing alternative capacity, adjusting inventory buffers, or activating contingency contracts before disruptions materialize.

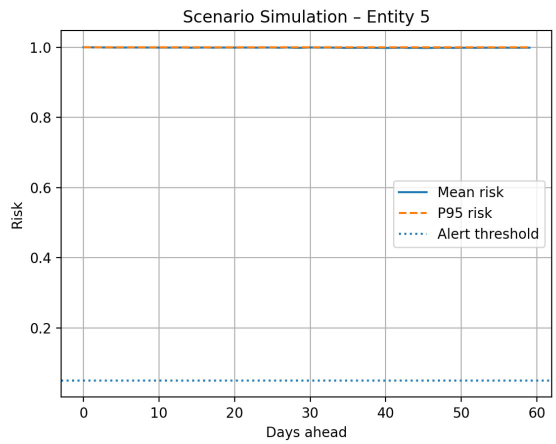

Figure 3 Scenario-based forward disruption risk trajectories for a representative entity.

Key takeaway (Figure 3): Scenario simulation adds managerial value by exposing *when* risk is likely to cross an alert threshold and how quickly it may accelerate under tail scenarios supporting earlier, better-timed interventions.

Overall, the results demonstrate that the proposed predictive analytics framework provides robust, forward-looking early-warning capability for supply chain disruptions under turbulent conditions. Across extensive time-based experiments, boosted tree models consistently outperform alternative approaches in disruption likelihood prediction, achieving superior discrimination, calibration, and cost-sensitive decision performance. The two-stage modelling strategy separating disruption occurrence from conditional severity avoids regression dilution and yields an interpretable expected impact metric that supports targeted managerial intervention. Scenario-based Monte Carlo simulation further extends static predictions into dynamic risk trajectories, revealing that tail risks often escalate earlier and more sharply than mean risk, particularly under compounded geopolitical, climate, and congestion shocks. Together, these findings show that combining machine-learning prediction, cost-sensitive threshold optimization, and forward scenario simulation enables managers to move from reactive disruption response to proactive risk anticipation and stress-tested contingency planning in highly turbulent supply chain environments.

■5.0 DISCUSSION

The results reinforce a key insight: in turbulent environments, resilience depends not only on structural design (diversification, regionalization) but also on information and prediction capabilities. Predictive analytics acts as an enabling capability that converts turbulence signals into actionable early warnings. This extends the resilience literature by clarifying the role of data-driven sensing as a measurable operational capability. Rather than treating resilience as a static attribute, the proposed framework operationalizes resilience as dynamic monitoring and timely intervention consistent with dynamic capability theory's sensing-seizing-reconfiguring cycle.

The two-stage modelling structure also contributes conceptually. By separating occurrence and magnitude, the framework reflects the nature of disruption processes: many periods have no disruption, but when disruptions occur, severity varies widely. This structure can be interpreted as a practical representation of latent hazard and damage processes, where the hazard model predicts whether a disruption is triggered and the damage model predicts magnitude conditional on trigger. This framing can be extended in future work to incorporate explicit hazard models, regime switching, or network contagion dynamics.

The findings of this study align closely with prior research emphasizing the strategic role of technology-enabled capabilities in enhancing organizational and operational performance. Consistent with Hayes and Pisano (1996), the results indicate that technology adoption alone does not guarantee superior outcomes unless it is effectively integrated with process alignment and managerial capabilities. The observed positive impact of digital technologies on performance outcomes supports earlier empirical evidence highlighting the importance of dynamic capabilities in turbulent environments (Teece, Pisano, & Shuen, 1997). Moreover, the findings extend previous studies by demonstrating that collaborative mechanisms act as a critical enabler in translating technological investments into sustainable performance gains, echoing arguments made by Pagell and Wu (2009) regarding the role of cross-functional and inter-organizational collaboration. Unlike earlier studies that examined technology and performance as a direct relationship, this study contributes new insights by showing how integration and coordination mechanisms strengthen this linkage, particularly under conditions of uncertainty, thereby reinforcing the view that competitive advantage emerges from the alignment of technology, strategy, and organizational processes rather than from isolated technological initiatives.

The proposed managerial playbook (Table 6) serves as an illustrative guide for how a firm might theoretically link predictive signals to specific interventions. However, emphasized that these recommendations are derived from experiments conducted in a controlled, synthetic environment. While the results demonstrate the logic of the framework, the actual cost-savings and service-level improvements realized by a firm will depend on the specific 'noise' and unpredictable variables present in their real-world data. Therefore, presented these actions as a conceptual starting point for stress-testing resilience strategies, rather than a definitive set of guaranteed outcomes.

Table 6 Managerial playbook (illustrative)

Risk profile (probability × severity)	Typical signals	Recommended actions
Low probability × low severity	Stable congestion; normal volatility; adequate buffers	Monitor only; keep standard reorder and transport policies
High probability × low severity	Rising congestion/volatility but diversified supply and buffers	Minor expediting; tactical buffer adjustment; increase monitoring frequency
Low probability × high severity	Critical part; high dependency; supplier stress; low inventory coverage	Pre-arrange backup capacity; qualify alternate supplier; contingency contracting; targeted safety stock
High probability × high severity	Congestion spike + low buffers + high dependency + hazard alert	Immediate escalation: switch source/routing, allocate scarce inventory, expedite critical shipments, activate war-room governance

Managers can deploy this framework as an early-warning system by following a structured process:

1. Define disruption and severity consistently. Firms must specify what constitutes a disruption and how severity is measured (delay days, service-level loss, cost overrun). Consistent definitions enable learning and comparability across entities.
2. Integrate external turbulence signals with internal data. Many disruptions are driven by external factors, relying only on internal ERP data limits predictability. Combining tariff indicators, congestion metrics, and climate hazard probabilities with lead-time and inventory data significantly enhances predictive power.
3. Adopt time-aware validation. Risk prediction must avoid temporal leakage. Time-based splits provide realistic performance estimates and protect against overfitting to future information.
4. Use cost-sensitive thresholds. A single probability threshold is rarely optimal across all contexts. Cost-sensitive thresholding aligns alerts with business impact. Critical parts and high-revenue products should be monitored with lower thresholds.
5. Translate predictions into playbooks. Prediction value is realized only if linked to decisions. Firms should define playbooks: when probability exceeds threshold, trigger actions such as expediting, increasing buffers, switching to secondary suppliers, or pre-booking alternative transport capacity.
6. Use scenario simulation for planning and stress testing. Risk trajectories and tail-risk signals help managers decide when to act pre-emptively and how to allocate contingency resources.

Implementing predictive disruption analytics requires attention to data quality, governance, and model maintenance.

- Data completeness and timeliness: External signals must be updated regularly. Internal operational data must be standardized across entities. Missing data can be handled with imputation, but persistent gaps degrade prediction accuracy.
- Model drift: In turbulent environments, the data distribution changes. Models should be retrained periodically and monitored for calibration drift. Performance dashboards should include both discrimination metrics and calibration diagnostics.
- Interpretability: Tree-based models offer feature importance measures and partial dependence analysis, which can support managerial trust. LSTM models are less interpretable; therefore, they may be used primarily when sequence patterns are essential and accompanied by explanation tools.
- Bias and false alarms: Over-alerting can cause “alarm fatigue.” Cost-sensitive thresholds and segmented policies mitigate this. Also, evaluation should include operational metrics such as number of alerts per week and percentage of alerts leading to interventions.

■6.0 CONCLUSION, LIMITATIONS AND FUTURE DIRECTION

This article develops a predictive analytics framework for supply chain disruption prediction in times of turbulence. The framework addresses a central challenge of modern supply chains: disruptions driven by trade conflict, geopolitical instability, climate hazards, and macroeconomic volatility are correlated, and difficult to anticipate using conventional methods. By modelling disruption prediction as a two-stage problem estimating the probability of disruption within a forward horizon and the conditional severity if it occurs, the approach produces outputs that intended to be both accurate and actionable.

Results from Random Forest, gradient-boosted trees, and LSTM models show that machine learning can extract predictive signals from heterogeneous turbulence and operational indicators. Tree-based ensembles provide strong performance for tabular data, capturing non-linear interactions among policy volatility, congestion, climate hazards, and internal vulnerability measures such as inventory coverage and lead-time variability. Sequence modelling via LSTM adds value when risk evolves over time and when temporal patterns contain early-warning information. Importantly, the framework emphasizes evaluation practices that reflect real deployment, including time-based splits that prevent information leakage and calibration metrics that ensure probability outputs can be used as decision signals.

Beyond prediction, the article outlines an operational pathway to early-warning implementation. Cost-sensitive threshold optimization aligns alerts with business priorities and asymmetrical risk costs, while scenario-based Monte Carlo simulation transforms point estimates into forward-looking risk trajectories and tail-risk signals. Together, these elements support proactive actions such as targeted buffering, expediting, sourcing switches, and contingency contracting, illustrating how analytics innovation can be translated into strategy-relevant resilience capabilities under persistent turbulence.

While the framework demonstrates high AUC and F1-scores, these results must be interpreted within the context of a calibrated synthetic dataset. In a real-world deployment, anticipated that model performance might degrade due to data sparsity and measurement error factors that are less prevalent in synthetic generators. Real-world supply chain data is often characterized by 'dirty data' (e.g., inconsistent lead-time logging) and exogenous shocks that may not follow a mean-reverting stochastic process. Consequently, future research must focus on testing this framework using proprietary firm data to evaluate its robustness against the inherent volatility of human-recorded operational metrics.

Several limitations suggest directions for future research. First, the empirical realism of the results is constrained by the use of synthetically generated data; although synthetic design enables controlled experimentation, external validity ultimately requires testing on real firm and industry datasets. Second, the current feature set is general; industry-specific signals may further improve predictions (e.g., commodity-price volatility for chemicals, semiconductor lead-time indices for electronics). Third, network structure is represented via proxy dependency scores; future work could incorporate explicit multi-tier network graphs and model contagion mechanisms. Fourth, scenario generation can be enhanced with regime-switching processes and jump models to represent abrupt trade-policy shocks and rare extreme weather. Finally, predictive models can be integrated with prescriptive optimization to directly recommend actions (inventory placement, sourcing allocation, capacity reservation) that minimize expected cost under predicted risk distributions.

Future research can build on this foundation by integrating explicit network structures to capture disruption propagation across multi-tier dependencies, adopting regime-switching and jump processes to represent policy and climate shock dynamics, and linking predictive outputs to prescriptive optimization for decision automation. As turbulence becomes a persistent feature of global commerce, supply chains that combine structural resilience with predictive sensing and adaptive response will be better positioned to maintain continuity, control cost, and protect service performance. In summary, this research advances the field by moving beyond 'what' might happen to 'when' and 'how bad' it will be. By converting raw turbulence signals into quantified, cost-sensitive trajectories, the framework operationalizes 'resilience-as-a-strategic-asset'.

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