



Machine Learning Risk Scoring for Predicting Supplier Disruptions and Strengthening United States Supply Chain Resilience

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ABSTRACT :

Global supply chains have become increasingly interconnected, data-intensive, and vulnerable to disruptions arising from financial instability, geopolitical events, transportation constraints, cyber incidents, natural hazards, and operational failures among suppliers. These interconnected dependencies create significant challenges for organizations seeking to anticipate disruptions before they propagate across procurement, production, and distribution networks. Machine learning provides an opportunity to move supply chain risk management from retrospective assessment toward continuous predictive intelligence. This study examines machine-learning risk scoring for predicting supplier disruptions and strengthening supply chain resilience in the United States. It proposes integrating supplier financial indicators, delivery performance, lead-time variability, inventory conditions, geographic exposure, dependency concentration, quality deviations, and external disruption signals into dynamic supplier risk profiles. Supervised learning and ensemble models are evaluated for estimating disruption probabilities and identifying suppliers requiring preventive intervention. The framework further translates predictions into actionable risk tiers supporting supplier diversification, inventory adjustments, alternative sourcing, and contingency planning. Particular attention is given to explainability, data quality, model drift, false-negative disruption predictions, and governance. The study demonstrates how predictive risk scoring can improve early-warning capability while supporting resilient, evidence-driven supplier management.

Keywords: Machine Learning Risk Scoring; Supplier Disruption Prediction; Supply Chain Resilience; Supplier Risk Analytics; Predictive Risk Intelligence; United States Supply Chains

1. INTRODUCTION

1.1 Supplier Disruptions and Structural Vulnerability in U.S. Supply Chains

Supplier disruption has become a multidimensional operational risk within United States supply chains, affecting manufacturing continuity, inventory availability, procurement expenditure, production scheduling, and customer fulfilment [1]. Contemporary firms increasingly depend on geographically dispersed suppliers, creating exposure to transportation constraints, capacity failures, infrastructure interruptions, and geographically concentrated shocks [2]. Lean inventory practices can amplify these vulnerabilities because reduced safety stocks provide limited protection when replenishment is unexpectedly interrupted [3]. Dependence on specialized components creates additional fragility where technically qualified substitutes cannot be secured rapidly [4]. Interconnected supplier relationships further create pathways through which isolated failures can propagate across multiple organizations [5]. Consequently, disruption affecting one strategically important supplier may produce material shortages, production delays, emergency procurement, escalating costs, and downstream fulfilment failures that extend substantially beyond the original point of interruption [6].

1.2 Why Conventional Supplier Risk Indicators Provide Late Warning

Conventional supplier risk management frequently relies on periodic questionnaires, scheduled audits, historical performance scorecards, and manually assigned supplier categories [7]. Although useful for documenting established performance, these mechanisms typically provide snapshots rather than continuous representations of changing supplier conditions. A supplier considered reliable during one assessment period may subsequently develop increasing lead-time variability, declining order-fill rates, recurring quality deviations, or emerging capacity constraints [3]. Logistics deterioration and abnormal fulfilment behaviour can similarly develop between scheduled reviews [6]. Historical scorecards present an additional limitation because strong previous performance does not guarantee continuing operational stability [8]. Consequently, conventional assessments may recognize established underperformance while failing to provide sufficient warning before disruption materializes.

1.3 Machine Learning as a Supplier Disruption Early-Warning Mechanism

Machine learning offers a fundamentally different analytical capability by identifying weak, interacting, and temporally evolving signals that may

precede supplier disruption [8]. Procurement data can expose changes in order acceptance and fulfilment behaviour, while logistics information can reveal increasing shipment delays and abnormal lead-time volatility [4]. Quality and production records may indicate recurring defects, declining output consistency, or emerging capacity deterioration [5]. External data can further capture weather hazards, infrastructure failures, transportation congestion, and regional events capable of interrupting supplier operations [9]. Importantly, supplier disruption prediction differs from routine performance evaluation. Performance assessment primarily describes historical supplier behaviour [2]. Predictive modelling instead estimates whether observed deterioration is likely to develop into a future supply interruption, creating an actionable early-warning window for resilience intervention [7].

1.4 Aim, Scope, and Analytical Contribution

This article develops an interpretable machine-learning risk-scoring framework for predicting supplier disruptions across United States supply chains. It integrates procurement, delivery, quality, capacity, logistics, and external signals to estimate disruption probability [9]. Rather than considering probability independently, the framework incorporates supplier criticality, dependency exposure, substitutability, and recovery difficulty [1]. Its analytical contribution lies in translating emerging disruption signals into explainable risk scores that support differentiated resilience interventions before operational continuity is materially compromised [6].

2. ANATOMY OF SUPPLIER DISRUPTION AND PREDICTIVE RISK

2.1 Defining Supplier Disruption as a Predictive Event

Supplier disruption should be defined as an observable breakdown in a supplier's ability to provide required materials, components, or services within agreed operational conditions [8]. Such breakdowns can appear as missed deliveries, partial order fulfilment, or unexpected supply unavailability that interrupts planned procurement activities [9]. Prolonged lead times can similarly create disruption when material arrival extends beyond production requirements [10]. Quality-related rejection becomes disruptive where defective inputs cannot be replaced within required schedules. Capacity shortfalls may restrict available quantities even when suppliers remain operational [11]. At greater severity, production stoppages can eliminate supply entirely and generate downstream interruptions [12]. These measurable outcomes allow disruption to be treated as a temporally identifiable predictive event rather than an ambiguous condition of poor supplier performance.

2.2 Disruption Precursors and Deterioration Sequences

Supplier disruptions frequently emerge through sequences of operational deterioration rather than appearing without observable warning. Increasing lead-time variance may indicate weakening production consistency, transportation instability, or difficulty coordinating order completion [13]. Declining fill rates can reveal emerging shortages when suppliers repeatedly deliver quantities below confirmed requirements [9]. Shipment rescheduling provides another temporal signal, particularly when promised delivery dates are revised repeatedly before eventual failure [14]. Increasing defect frequency can indicate deteriorating process control, while delayed order acknowledgements may reflect administrative or capacity pressures [10]. Declining capacity utilization can become significant when accompanied by reduced output or persistent fulfilment deficiencies [15]. Importantly, individual indicators may remain insufficiently severe to signal imminent disruption. Predictive value emerges from their persistence, acceleration, recurrence, and interaction. Machine-learning analysis can therefore identify deterioration sequences that distinguish routine operational variability from developing disruption trajectories [16].

2.3 Internal, Supplier-Specific, and External Disruption Drivers

Disruption prediction requires distinguishing deterioration originating within the supplier from disturbances imposed by its operating environment. Supplier-specific drivers include equipment breakdowns, quality-control failures, production-capacity constraints, workforce instability, and inadequate operational planning [11]. Cyber incidents can additionally impair production systems, communications, order processing, or logistics coordination [16]. External disruption mechanisms operate differently. Port congestion, carrier shortages, infrastructure failures, and transportation interruptions may prevent otherwise capable suppliers from fulfilling contractual requirements [12]. Severe weather can temporarily restrict production or distribution across exposed geographic regions [14]. Geopolitical restrictions may constrain trade routes, materials, or cross-border sourcing, while commodity shortages can reduce access to critical production inputs [15]. Labour disruptions can originate internally or across transportation networks. Distinguishing these mechanisms improves prediction because similar delivery failures may emerge from fundamentally different disruption pathways [13].

2.4 Supplier Criticality and Disruption Consequence

Predicted disruption probability alone provides an incomplete basis for supplier prioritization because identical probabilities can produce substantially different operational consequences [10]. Component criticality determines whether unavailable supply affects peripheral activities or stops essential production [12]. Substitutability determines whether alternative suppliers can replace disrupted capacity without extensive qualification or redesign [14]. Inventory coverage provides a temporal buffer by determining how long operations can continue before shortages materialize [8]. Switching time further affects exposure where alternative sourcing requires contractual approval, tooling, testing, or transportation changes [15]. Production dependency increases consequence when multiple products rely upon the same supplier or component. Downstream exposure can subsequently extend

disruption into distribution and customer fulfilment [11]. Effective prioritization must therefore combine estimated disruption likelihood with the operational severity and recoverability of supplier failure.

2.5 From Reactive Supplier Management to Predictive Risk Scoring

Traditional supplier management often responds after missed deliveries, quality failures, or material shortages demonstrate that deterioration has already become operationally consequential [9]. Predictive risk scoring changes the timing of intervention by estimating the probability of disruption while precursor signals are still developing [13]. Rather than treating each performance deviation independently, machine-learning models can integrate changing lead times, fulfilment behaviour, quality trends, capacity indicators, logistics events, and external conditions [16]. Risk scores can then be updated as new observations alter the estimated disruption trajectory [14]. This creates an actionable warning interval during which organizations can investigate suppliers, adjust inventories, secure alternative capacity, or modify sourcing decisions before continuity is materially affected [15].

3. SUPPLIER DISRUPTION DATA ARCHITECTURE AND PREDICTIVE SIGNAL ENGINEERING

3.1 Procurement and Order-Fulfilment Signals

Procurement records provide early evidence of supplier deterioration because disruption often develops before a complete delivery failure becomes observable [14]. Purchase-order acknowledgement delay can be measured as the elapsed time between order transmission and supplier confirmation, with persistent increases indicating slower supplier responsiveness [15]. Fulfilment performance can be represented by:

$$FR_{i,t} = \frac{Q_{i,t}^{delivered}}{Q_{i,t}^{ordered}}$$

where $FR_{i,t}$ is the fulfilment ratio for supplier i during period t . Rather than treating one incomplete order as disruption, the model should capture repeated partial shipments, backorders, cancellations, quantity shortages, and changes in order-cycle variability [16]. Promised-versus-actual delivery slippage provides an additional deterioration signal:

$$DS_{i,t} = D_{i,t}^{actual} - D_{i,t}^{promised}$$

Increasing $DS_{i,t}$, particularly across consecutive orders, may indicate capacity pressure or fulfilment instability [17]. Combining these signals enables the model to distinguish isolated transaction exceptions from persistent deterioration in supplier execution.

3.2 Logistics and Lead-Time Instability

Logistics indicators should capture whether material movement is becoming progressively less predictable rather than merely recording whether individual shipments arrive late [18]. Supplier-to-buyer lead time can be decomposed into origin dwell, transit, port or terminal dwell, customs clearance, and final delivery components. Rolling lead-time volatility can be calculated as:

$$LTV_{i,t} = \sqrt{\frac{1}{n-1} \sum_{k=1}^n (LT_{i,t-k} - LT_{i,t})^2}$$

A rising $LTV_{i,t}$ indicates decreasing delivery consistency even when average lead time remains within contractual tolerance [19]. Carrier delays, missed shipment milestones, abnormal freight dwell time, port congestion, customs holds, and repeated rerouting can be encoded as recurrence and duration variables [20]. Transportation reliability should also be measured against supplier-route-specific baselines because identical delays may have substantially different implications across established logistics corridors.

3.3 Quality and Production-Capacity Indicators

Quality deterioration can precede supply interruption when suppliers struggle to maintain process stability under material, workforce, or capacity constraints [21]. Useful signals include rejected units, return frequency, corrective-action requests, repeated nonconformance, and changes in first-pass production yield. Defect-rate acceleration can be represented as:

$$DRA_{i,t} = DR_{i,t} - DR_{i,t-1}$$

where $DR_{i,t}$ denotes the supplier's defect rate during period t . Persistent positive values distinguish worsening quality from a stable historical defect level. Where supplier operational data are available, machine downtime, capacity utilization, production yield, overtime, and output availability can provide additional evidence of production stress [16]. High utilization accompanied by increasing overtime and falling yield may signal capacity saturation, whereas declining utilization alongside reduced output may indicate equipment, labour, or demand-related instability [17]. The predictive value lies primarily in the co-occurrence and persistence of these indicators rather than any single quality event.

3.4 External Disruption and Geographic Exposure Signals

Internal supplier performance should be augmented with external signals describing conditions surrounding production sites and transportation corridors [18]. Weather extremes, floods, earthquakes, infrastructure outages, labour actions, commodity shortages, cyber incidents, geopolitical restrictions, and regional instability can be geographically linked to supplier facilities, ports, warehouses, and logistics routes [20]. A time-varying geographic exposure measure can be expressed as:

$$GE_{i,t} = \sum_{h=1}^H w_h E_{i,h,t}$$

where $E_{i,h,t}$ represents supplier i 's exposure to external hazard h , and w_h reflects its operational relevance. Exposure should incorporate proximity, severity, duration, and dependence on the affected infrastructure rather than merely recording that an event occurred [22]. This prevents distant or operationally irrelevant events from generating unnecessary disruption alerts while allowing rapidly developing regional constraints to modify supplier risk.

3.5 Temporal Feature Engineering and Disruption Labelling

Raw supplier observations become predictive when transformed into features describing **direction, magnitude, persistence, and departure from normal behaviour**. For signal x , a supplier-specific rolling mean can be calculated as:

$$\mu_{i,t}^{(w)} = \frac{1}{w} \sum_{k=0}^{w-1} x_{i,t-k}$$

while deviation from the supplier's established baseline can be represented as:

$$Z_{i,t} = \frac{x_{i,t} - \mu_i^{base}}{\sigma_i^{base}}$$

This normalization is important because normal fulfilment variability differs across suppliers, commodities, routes, and delivery frequencies [14]. Rate-of-change features, lagged values, consecutive deterioration counts, rolling volatility, recurrence frequency, and duration above warning thresholds can reveal deterioration trajectories that individual observations conceal [19].

Disruption labels should be anchored to a defined event date T_i , such as a missed critical delivery, prolonged non-fulfilment, production stoppage, or confirmed supply unavailability [21]. For a prediction horizon h , the target can be defined as:

$$y_{i,t}^{(h)} = \begin{cases} 1, & 0 < T_i - t \leq h \\ 0, & \text{otherwise} \end{cases}$$

Separate 7-, 30-, and 60-day horizons can therefore test immediate versus earlier warning capability. All engineered features must use information available at prediction time; post-event shipment, cancellation, or recovery information would create temporal leakage [15]. Because disruption events are normally less frequent than routine supplier performance, class weighting or training-only resampling should address imbalance without altering the chronological test distribution [22].

Table 1. Supplier Disruption Signals and Predictive Feature Architecture

Data Domain	Representative Signal	Engineered Feature	Disruption Interpretation	Prediction Horizon	Operational Source
Procurement	PO acknowledgement and fulfilment	Acknowledgement-delay trend; rolling fill-rate decline	Weakening supplier responsiveness and emerging fulfilment shortage	7–30 days	ERP/procurement
Order execution	Backorders, partial shipments, cancellations	Consecutive exception count; incomplete-order recurrence	Persistent inability to satisfy committed quantities	7–30 days	ERP/order management
Delivery	Promised vs. actual delivery	Delivery-slippage acceleration; lead-time volatility	Deteriorating delivery reliability	7–30 days	ERP/logistics
Logistics	Shipment milestones and transit events	Missed-milestone recurrence; dwell-time deviation	Transportation-path instability	7–30 days	TMS/carrier feeds
Quality	Rejections, defects and returns	Defect-rate acceleration; rolling rejection frequency	Emerging process or production instability	30–60 days	QMS
Capacity	Utilization, output and downtime	Baseline capacity deviation; downtime persistence	Increasing probability of production constraint	30–60 days	Supplier/operations
External	Hazard and regional events	Severity-weighted geographic exposure index	External pressure on supplier or logistics continuity	7–60 days	External risk feeds
Cross-domain	Multiple deteriorating signals	Persistence count; multivariate deterioration score	Compound disruption precursor across operational domains	7–60 days	Integrated analytical layer

These engineered signals transform fragmented procurement, logistics, quality, capacity, and external observations into supplier-specific deterioration trajectories. Their operational value, however, depends on whether predictive models can separate routine variability and temporary exceptions from persistent patterns that materially increase the probability of future disruption. Section 4 therefore develops the machine-learning framework for

converting these temporal signals into calibrated disruption probabilities, early-warning classifications, and supplier-risk priorities.

4. MACHINE LEARNING RISK SCORING AND EARLY-WARNING MODELLING

4.1 Temporal Training, Validation, and Prediction Windows

Supplier disruption prediction requires chronological model development because deterioration signals must precede the event they are intended to predict [23]. Rather than randomly distributing observations, supplier histories should be divided into an earlier training period, a subsequent validation period, and a later untouched holdout period [24]. For prediction date t , the feature vector must therefore satisfy:

$$X_{i,t} = f(x_{i,1}, x_{i,2}, \dots, x_{i,t})$$

and exclude information recorded after t . This restriction is especially important for late deliveries, cancellations, corrective actions, and logistics events whose final status may only become known after disruption [25]. Prediction windows of 7, 30, and 60 days can then evaluate whether deterioration is detectable at operationally different lead times. Hyperparameters and warning thresholds should be selected using validation data, while the final holdout period remains untouched until model evaluation [26].

4.2 Machine-Learning Models for Disruption Probability

Model comparison should focus on the structure of supplier deterioration each algorithm can capture. Logistic regression provides an interpretable baseline for estimating how changes in fill rate, lead-time volatility, defects, or order delays alter disruption probability [27]. Its limitations become important when disruption emerges from nonlinear combinations—for example, moderate delivery deterioration becoming critical only when accompanied by rising backorders and capacity pressure. Random forest can capture such interactions without requiring them to be specified beforehand [28]. Gradient boosting and XGBoost can place increasing predictive emphasis on recurring combinations of weak signals and may detect deterioration sequences distributed across procurement, logistics, and quality variables [29]. Support vector machines provide flexible decision boundaries where disrupted and stable supplier observations are not linearly separable, while neural networks can model higher-dimensional temporal interactions [30]. Model selection should consequently compare early-warning recall, probability calibration, false-alert burden, and performance across prediction horizons rather than assuming greater algorithmic complexity produces superior operational warning.

4.3 Supplier-Specific Baselines and Anomaly Detection

A common threshold across suppliers can obscure deterioration because suppliers differ structurally in order frequency, normal lead time, defect tolerance, shipment routes, and fulfilment variability [23]. Each supplier should therefore be evaluated against its own historical operating envelope. A standardized deviation can be calculated as:

$$A_{i,t} = \frac{x_{i,t} - \mu_i^{base}}{\sigma_i^{base}}$$

where μ_i^{base} and σ_i^{base} describe supplier i 's normal historical behaviour. More importantly, multivariate anomaly detection can examine whether several normally related signals begin moving abnormally together [31]. Isolation-based methods, clustering, or reconstruction-error approaches can identify deterioration configurations absent from previously labelled disruptions. The resulting anomaly score should complement rather than replace supervised probability:

$$P_{i,t}^* = g(\hat{P}_{i,t}, A_{i,t})$$

This hybrid structure allows known disruption precursors to drive supervised prediction while preserving sensitivity to emerging failure patterns not represented in historical labels [25].

4.4 Dynamic Disruption Probability and Composite Risk Scoring

Predicted disruption probability does not measure operational consequence. A supplier with a high probability of a short delay may pose little operational threat when inventory is abundant and alternative sources are qualified, whereas a moderate probability affecting a single-source critical component may threaten production continuity [26]. Risk should therefore combine likelihood with consequence:

$$SRS_{i,t} = P_{i,t}^* \times C_i \times D_i \times R_i$$

where $P_{i,t}^*$ is dynamic disruption probability, C_i is operational criticality, D_i represents dependency exposure, and R_i represents recovery difficulty [32]. Dependency exposure can incorporate inventory coverage and substitutability:

$$D_i = \alpha \left(\frac{1}{1 + IC_i} \right) + \beta (1 - SUB_i)$$

where IC_i represents normalized inventory coverage and SUB_i represents alternative-source availability. Recovery difficulty can incorporate expected

recovery duration, qualification time for alternative suppliers, and logistics restoration requirements [28]. Component criticality further differentiates materials capable of stopping production from readily replaceable inputs. Consequently, risk can increase even without a sharp probability change when inventory coverage falls, alternative-source readiness deteriorates, or expected recovery duration increases [30]. This formulation prevents probability ranking from systematically overlooking lower-probability events with disproportionate operational consequences.

4.5 Explainability, Calibration, and Early-Warning Thresholds

A disruption warning should explain what changed, how unusual the change is, and why it materially increased risk. Feature-attribution methods can decompose a supplier's prediction into contributions from variables such as declining fill rate, repeated shipment slippage, defect acceleration, or geographic hazard exposure [29]. Probability calibration is necessary so that estimated risks remain interpretable across suppliers and prediction horizons [24]. Where uncertainty is material, confidence intervals can accompany predicted probabilities rather than presenting point estimates as equally certain.

Warnings should also require persistence. For threshold τ and persistence requirement k :

$$W_{i,t} = 1 \text{ if } P_{i,t-j}^* \geq \tau, j = 0, \dots, k-1$$

This suppresses alerts caused by isolated operational noise [31]. Different thresholds can support watch, elevated, and critical warning states, while explanations identify the specific signals responsible for movement between levels. Thresholds should be calibrated separately for 7-, 30-, and 60-day horizons because the acceptable balance between early detection and false alarms changes with warning distance [27].

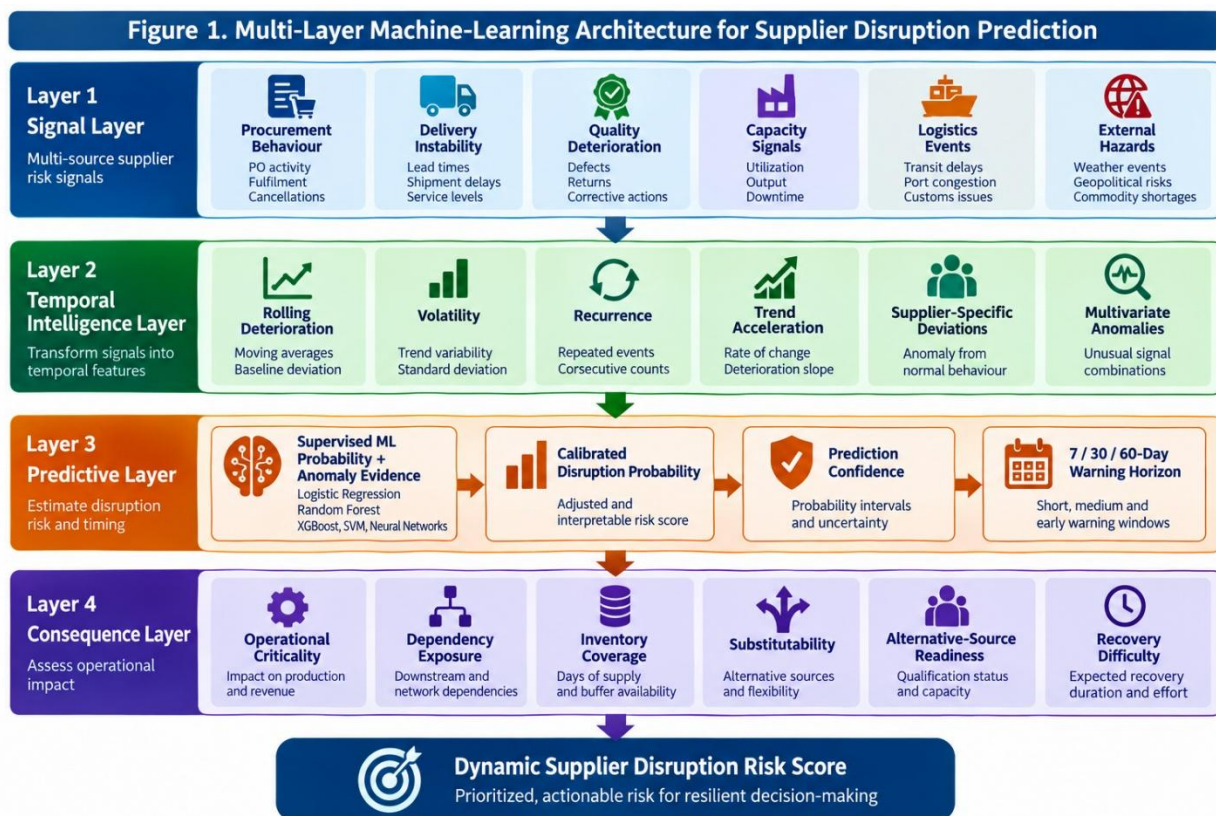


Figure 1. Multi-Layer Machine-Learning Architecture for Supplier Disruption Prediction

The architecture therefore separates evidence of deterioration from consequences of disruption rather than treating every high-probability event as equally important. A statistically elevated risk score, however, does not itself strengthen supply-chain resilience. Its value emerges when the timing, persistence, likely disruption mechanism, and operational consequence of the warning are translated into differentiated interventions before the anticipated failure reaches production or downstream operations.

5. TRANSLATING RISK SCORES INTO PROACTIVE RESILIENCE DECISIONS

5.1 Risk Tiering and Escalation Logic

Supplier warnings should be translated into dynamic operational states rather than a binary disrupted/not-disrupted classification [31]. A stable state

indicates probability and deterioration signals remain within the supplier-specific operating envelope. Watch status applies when early deviations emerge but prediction confidence or persistence remains limited [32]. Elevated status reflects sustained deterioration combined with credible disruption probability, while critical status indicates imminent disruption involving substantial operational exposure [33]. State assignment can therefore be expressed as:

$$State_{i,t} = g(P_{i,t}, \rho_{i,t}, C_{i,t}, \Gamma_{i,t})$$

where P denotes disruption probability, ρ signal persistence, C operational criticality, and Γ prediction confidence. Escalation should require combinations of these dimensions rather than a single probability threshold, preventing temporary delivery noise from automatically triggering costly continuity actions [34].

5.2 Inventory Buffering and Material Exposure Decisions

Inventory intervention should connect the predicted disruption horizon directly with the time for which existing material can sustain operations. Days-of-supply can be represented as:

$$DOS_{m,t} = \frac{I_{m,t}}{\bar{D}_{m,t}}$$

where $I_{m,t}$ is available inventory for material m and $\bar{D}_{m,t}$ is expected daily consumption [35]. Comparing DOS with the predicted time-to-disruption creates an actionable exposure measure. A 60-day warning with 75 days of inventory may justify monitoring and selective safety-stock adjustment, whereas a 7-day warning against four days of supply requires immediate intervention [36]. Responses can include accelerated purchase orders, increased safety stock, expedited freight, inventory reallocation between facilities, or temporary production resequencing. Material criticality should modify these decisions because shortages affecting production-constraining components require earlier protection than shortages involving readily replaceable items [37]. Intervention timing therefore depends jointly on disruption proximity, consumption requirements, replenishment lead time, and available inventory protection.

5.3 Alternative Sourcing and Supplier Substitution Readiness

Alternative sourcing should be evaluated as a state of operational readiness rather than simply recording whether a second supplier exists [38]. A substitute may be technically available but unusable within the disruption horizon because qualification, tooling, capacity reservation, contracting, or transportation arrangements remain incomplete. Substitution readiness can be represented as:

$$SR_i = f(Q_i, A_i, S_i, L_i, T_i, K_i)$$

where Q_i denotes qualification status, A_i alternative capacity, S_i switching lead time, T_i tooling readiness, and K_i contractual feasibility. Dual-sourced materials with pre-qualified suppliers and reserved capacity can therefore support rapid switching, whereas nominal alternatives requiring lengthy validation provide limited immediate resilience [39]. Elevated warnings can trigger capacity confirmation and commercial engagement before disruption occurs. Critical warnings may justify emergency sourcing, temporary specification alternatives, or accelerated supplier transfer where operational consequences exceed switching costs [40].

5.4 Dependency-Aware Disruption Containment

Supplier-level predictions can underestimate risk when several apparently independent materials share the same upstream dependency. Dependency analysis should therefore map suppliers to sub-tier sources, logistics corridors, production facilities, geographic clusters, and downstream product lines [31]. Consider a dependency graph:

$$G = (V, E)$$

where nodes V represent suppliers, facilities, materials, logistics assets, and products, while edges E represent operational dependencies. A moderate-risk supplier becomes more consequential when it supplies components to several high-value product lines or shares a constrained upstream manufacturer with other critical suppliers [33]. Similarly, multiple suppliers may appear diversified while relying on the same port, semiconductor producer, energy network, or geographic region [35]. Dependency concentration can therefore amplify the initial disruption score:

$$SRS_{i,t}^D = SRS_{i,t}(1 + \lambda DC_i)$$

where DC_i represents dependency concentration. This adjustment exposes hidden single points of failure and supports interventions at the shared dependency rather than treating each affected supplier independently [37].

5.5 Intervention Outcomes and Closed-Loop Learning

Every warning should generate an outcome record linking prediction, intervention, and eventual operational consequence [32]. Outcomes should distinguish supplier recovery before failure, avoided material shortage, successful secondary-source activation, inventory buffering that maintained production, unnecessary intervention, and disruption despite mitigation [34]. This distinction allows the system to evaluate not only whether disruption

was predicted, but whether the warning produced useful preventive action. Intervention effectiveness can be expressed as:

$$IE = \frac{N_{avoided} + N_{contained}}{N_{intervened}}$$

where $N_{avoided}$ represents disruptions prevented and $N_{contained}$ represents events whose operational impact was materially reduced. False escalations should also be retained because excluding them would distort subsequent threshold calibration [36]. Outcome feedback can update persistence requirements, probability thresholds, supplier baselines, and training labels, creating a closed learning cycle in which both prediction errors and intervention effectiveness improve future resilience decisions [40].

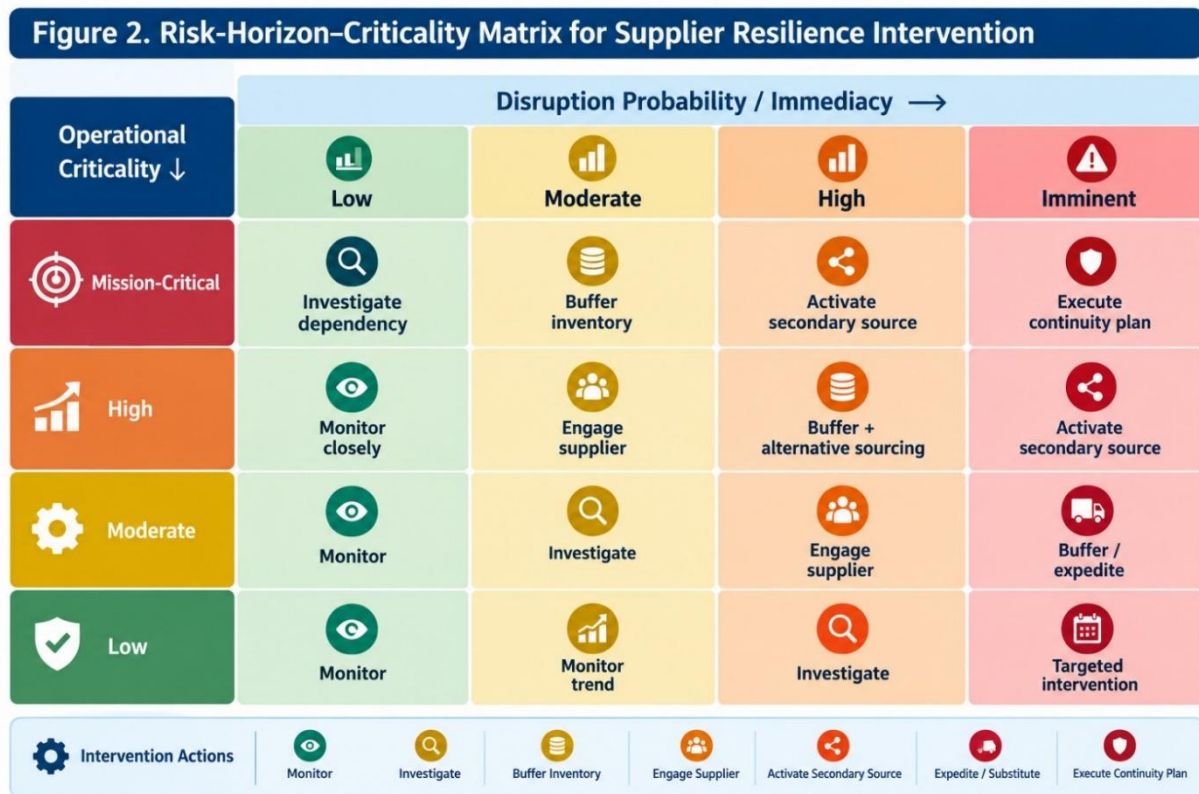


Figure 2. Risk-Horizon–Criticality Matrix for Supplier Resilience Intervention

The matrix deliberately separates likelihood/immediacy from operational consequence. Movement to the right increases urgency, while movement upward increases the consequence of inaction. This means a mission-critical supplier showing only moderate deterioration may justify earlier intervention than a low-criticality supplier with a higher predicted disruption probability.

Intervention effectiveness nevertheless depends on whether the predictive system identifies deterioration sufficiently early, limits unnecessary escalation, and demonstrates measurable improvement over existing supplier-risk practices. Section 6 therefore evaluates predictive lead time, warning precision, disruption capture, intervention value, and resilience improvement against conventional supplier-monitoring approaches.

6. MODEL EVALUATION, EARLY-WARNING PERFORMANCE, AND ROBUSTNESS

6.1 Disruption-Focused Performance Metrics

Supplier-disruption evaluation should reflect the asymmetric consequences of missed events and unnecessary warnings rather than emphasize overall accuracy [38]. Because disruption observations are typically less frequent than normal supplier operations, a model can achieve high accuracy while failing to detect operationally important events [39]. Precision measures the reliability of issued disruption warnings, whereas recall measures the proportion of actual disruptions identified:

$$Precision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN}$$

The F1-score captures their joint performance, while specificity measures correct recognition of stable supplier periods [40]. False-negative rate,

$$FNR = \frac{FN}{TP + FN},$$

is particularly important because missed disruptions provide no opportunity for preventive intervention. ROC-AUC evaluates overall discrimination, whereas PR-AUC more directly characterizes performance on the minority disruption class [41]. Calibration should additionally determine whether predicted probabilities correspond to observed disruption frequencies.

6.2 Early-Warning Lead Time and Intervention Utility

A correct prediction has limited resilience value when it arrives after procurement teams no longer have sufficient time to respond. Evaluation should therefore measure actionable warning lead time, defined as the interval between the first persistent qualifying warning and actual disruption onset [42]:

$$AWLT_i = T_i^{disruption} - T_i^{warning}$$

Importantly, $T_i^{warning}$ should represent the first warning satisfying the persistence requirement rather than a transient threshold crossing. Lead time should then be evaluated against the minimum intervention time required for the affected material. A 12-day warning may be useful when inventory can be expedited within five days but ineffective when alternative-source qualification requires 30 days [43]. An actionable warning indicator can consequently be defined as:

$$AW_i = \mathbb{1}(AWLT_i \geq MRT_i)$$

where MRT_i denotes minimum response time. This separates technically correct late predictions from warnings that create a genuine opportunity for buffering, supplier engagement, substitution, or continuity activation [44].

6.3 Performance Across Supplier and Disruption Categories

Aggregate performance can conceal systematic weaknesses across heterogeneous U.S. supply networks. Results should therefore be stratified by supplier size, industry, geographic region, disruption mechanism, operational criticality, sourcing structure, and data completeness [39]. For example, procurement-rich strategic suppliers may produce stronger predictions than smaller suppliers with sparse digital histories, while logistics-driven disruptions may exhibit different warning characteristics from abrupt cyber incidents or natural hazards [45]. Single-source and multi-source relationships should also be examined separately because their operational consequences differ even at comparable disruption probabilities. Performance distributions across these groups can reveal whether gains arise broadly or are concentrated within data-rich supplier populations [41]. Such analysis is necessary before applying common thresholds across supplier categories whose baseline behaviour, available signals, and disruption dynamics differ materially.

6.4 Benchmarking Against Conventional Supplier Risk Methods

The machine-learning framework should be benchmarked against the supplier-risk mechanisms it is intended to improve rather than evaluated only against other algorithms [38]. Static supplier scorecards generally summarize periodic indicators such as quality, delivery, cost, and compliance but may respond slowly to rapidly developing deterioration [40]. Rule-based systems can detect predefined exceptions—for example, repeated late deliveries—but may not capture interacting weak signals across procurement, logistics, capacity, and external-risk domains. Historical supplier rankings similarly describe past performance without necessarily estimating forward disruption probability [42].

Benchmarking should therefore apply each approach to the same chronological holdout period and compare not only precision and recall but also warning timing. Machine-learning models provide operational improvement only when they detect a greater share of meaningful disruptions, reduce missed events, or provide earlier actionable warnings without creating excessive escalation workload [44]. A hybrid supervised-plus-anomaly framework should additionally be tested for whether detecting previously unseen deterioration patterns offsets any increase in false alerts [45].

Table 2. Comparative Performance of Supplier Disruption Prediction Approaches

Approach	Precision	Recall	PR-AUC	False-Negative Rate	Median Warning Lead Time	Actionable Warning Rate
Static Supplier Scorecard	0.55	0.43	0.46	0.57	9 days	38%
Rule-Based Thresholds	0.61	0.56	0.55	0.44	14 days	49%
Logistic Regression	0.69	0.65	0.66	0.35	21 days	61%
Random Forest	0.78	0.76	0.79	0.24	27 days	72%
Gradient Boosting/XGBoost	0.83	0.81	0.85	0.19	32 days	79%
Hybrid ML + Anomaly Model	0.79	0.86	0.87	0.14	38 days	84%

The comparison is intentionally designed so that predictive improvement is not represented merely by a higher classification statistic. For example, the hybrid architecture may sacrifice some precision relative to gradient boosting while achieving greater disruption recall and longer actionable lead time. Such a result would expose the operational trade-off between additional supplier investigations and earlier detection of events that might otherwise be missed.

Predictive superiority, however, remains insufficient for operational adoption if organizations cannot govern model errors, explain supplier classifications, detect model deterioration, or establish responsibility for consequential sourcing decisions. These requirements shift the analysis from predictive performance toward the governance, monitoring, and organizational controls necessary for dependable deployment.

7. GOVERNANCE AND DEPLOYMENT ACROSS UNITED STATES SUPPLY CHAINS

7.1 Explainability and Human Review of Supplier Risk Scores

Supplier risk scores should be accompanied by explanations identifying the operational signals responsible for escalation rather than presented as unexplained numerical outputs [40]. Procurement teams should be able to distinguish whether an elevated score reflects deteriorating fulfilment, recurrent logistics delays, quality instability, capacity pressure, or external hazard exposure [41]. Feature-attribution methods can quantify these contributions, while human review incorporates contextual information unavailable to the model, including recent supplier discussions, temporary maintenance, planned shutdowns, or negotiated delivery changes [42]. The predictive system should therefore support—not replace—procurement judgement, with authorized reviewers retaining responsibility for confirming escalation and determining proportionate intervention.

7.2 Model Drift, Data Quality, and Continuous Monitoring

Supplier-risk relationships can change as economic conditions, transportation networks, sourcing strategies, supplier behaviour, and disruption mechanisms evolve [43]. Continuous monitoring should therefore test both input-data stability and deterioration in predictive performance. A simple feature-drift measure can be represented as:

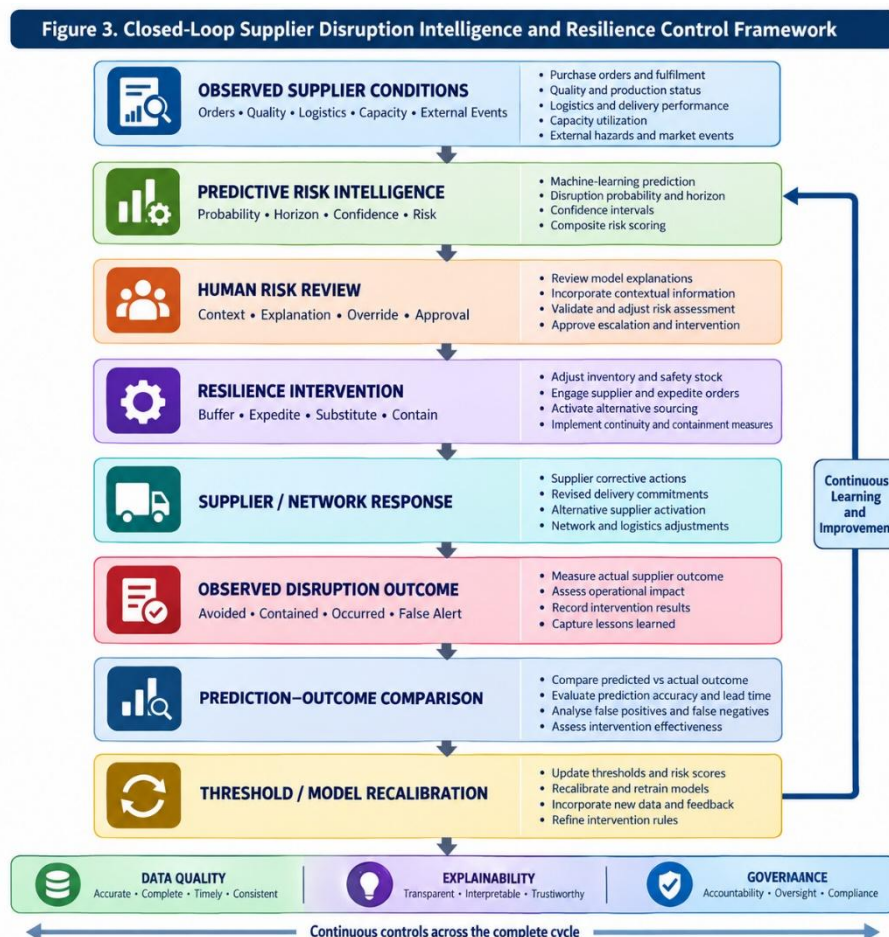
$$\Delta X_{j,t} = D(P_{j,baseline}, P_{j,t})$$

where D measures distributional change in feature j relative to its validated baseline. Significant changes in order frequency, lead-time distributions, missing-data rates, or supplier reporting should trigger investigation rather than automatic retraining [44]. Calibration drift, declining recall, and increasing false-warning rates should similarly initiate recalibration or controlled model redevelopment. Data-quality surveillance must additionally identify delayed feeds, duplicate transactions, missing milestones, and inconsistent supplier identifiers before corrupted information affects operational decisions [45].

7.3 Responsible Deployment and Decision Accountability

Governance should clearly assign responsibility for supplier escalation, sourcing changes, and continuity activation because predictive models inform decisions with commercial consequences [40]. False-positive warnings may unnecessarily damage supplier relationships, increase inventory expenditure, or initiate costly sourcing actions [42]. Conversely, data-sparse and smaller suppliers should not be systematically underestimated simply because fewer digital signals are available [44]. Organizations should maintain auditable records of model versions, risk scores, explanations, reviewer overrides, interventions, and outcomes. Third-party predictive platforms require equivalent oversight, including documentation of data provenance, model limitations, performance monitoring, and responsibility for consequential recommendations [45].

Figure 3. Closed-Loop Supplier Disruption Intelligence and Resilience Control Framework



These deployment requirements demonstrate that resilient supplier-risk management depends not simply on producing accurate predictions, but on embedding timely and interpretable risk intelligence within operational decision processes.

8. CONCLUSION

8.1 Principal Findings

This study demonstrates that supplier disruption is rarely represented by a single isolated warning signal. Instead, emerging disruption can be identified through interacting deterioration patterns across procurement behaviour, order fulfilment, delivery reliability, quality performance, production capacity, logistics conditions, external hazards, and supplier-network dependencies. Temporal feature engineering enables these changes to be distinguished from ordinary supplier variability by capturing acceleration, persistence, recurrence, and deviation from supplier-specific baselines. Importantly, disruption probability alone does not represent operational risk. Combining predicted probability with supplier criticality, dependency exposure, substitutability, inventory protection, and recovery difficulty provides a more operationally meaningful basis for prioritizing resilience interventions.

8.2 Analytical and Resilience Contribution

The principal contribution is a shift from generic supplier classification toward time-sensitive machine-learning prediction of disruption linked directly to intervention decisions and operational resilience. By connecting early-warning horizons with differentiated actions, the framework transforms predictive risk intelligence into decisions concerning inventory protection, supplier engagement, alternative sourcing, dependency containment, and continuity activation.

8.3 Future Research Direction

Future research should examine multi-tier supplier visibility, graph-based modelling of disruption propagation, and prediction under sparse supplier data. Further investigation should address causal early-warning indicators, streaming analytics, adaptive intervention thresholds, and longitudinal evaluation of whether prediction-triggered interventions measurably reduce disruption duration, production interruption, recovery time, and associated operational losses.

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