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A Business-Intelligence-Driven Early-Warning System for Supply Disruption Risk in U.S. Power-Systems Manufacturing

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Abstract
Delivery failure is often visible only after upstream supplier stress has already constrained production. This paper develops a business-intelligence framework for supply-disruption early warning that combines transactional indicators, external context, exposure and owned mitigation actions. Supplier-part signals are normalized against information available at the scoring date and qualified using consistent supplier-week contingency counts and mitigation lead times. An inverse noise-to-signal weighting scheme produces a risk propensity index, which requires separate calibration before it can be interpreted as a disruption probability. A synthetic panel of 80 supplier-part pairs over 156 weeks illustrates threshold and workload trade-offs. The reported backtest is a design demonstration, not evidence of performance at a specific manufacturer. The contribution is an auditable connection between signals, decision timing and mitigation responsibility. Validation requires temporally separated training and testing, a complete simulation specification, alarm-episode definitions and event-level evaluation. The framework provides a basis for comparing useful warning time with the false-alert workload that procurement and engineering teams can manage.

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1. Introduction

The U.S. electric power sector is in the middle of its largest build-out in decades. Load growth from data centers, manufacturing reshoring and electrification, together with transmission expansion and the replacement of aging assets, has pushed demand for grid equipment well above the capacity of the domestic manufacturing base. The Department of Energy's 2022 supply chain assessment for large power transformers and high-voltage direct current systems identified heavy import dependence, limited domestic grain-oriented electrical steel production and long qualification cycles as structural vulnerabilities (U.S. Department of Energy, 2022b). By 2023 and 2024, industry reporting described transformer lead times stretching beyond two years in many categories, while switchgear, breakers and power electronics experienced extended and erratic delivery promises.

For manufacturers that build this equipment, the result is a supply base in which a single late lot of laminations, a molded component, a vacuum interrupter or a microcontroller can idle a production line that serves utility customers with firm in-service dates. Disruption is costly: firms that announce supply chain glitches experience significant and persistent declines in shareholder value and increases in equity risk (Hendricks & Singhal, 2005). Yet in many plants, disruption detection still depends on the expedite call, the missed receipt or the shortage report. These are lagging indicators. By the time they fire, the cheapest mitigation

options, such as qualifying an alternate source, pulling forward a buy or re-sequencing production, have often expired.

At the same time, most manufacturers already own the raw material for earlier warning. Enterprise resource planning (ERP) systems record every promise date and receipt. Supplier portals capture acknowledgment times. Procurement teams subscribe to commodity, freight and supplier financial data. BI platforms aggregate these feeds into dashboards. What is usually missing is not data but a disciplined method for deciding which signals actually lead disruption, by how much, how to combine them, and what action each level of risk should trigger.

Prior research offers several building blocks for such a method. Supply chain risk management (SCRM) research has long distinguished between risk identification, assessment, mitigation and monitoring. Chopra and Sodhi (2004) categorized disruption, delay, systems, forecast, intellectual property, procurement, receivables, inventory and capacity risks, and argued that mitigation must be tailored to the risk driver. Tang (2006) reviewed quantitative models for supply chain risk, and Sheffi (2005) emphasized redundancy and flexibility as foundations of the resilient enterprise. Craighead *et al*. (2007) showed that disruption severity depends on supply network density, complexity and node criticality, as well as on recovery and warning capabilities. Wagner and Bode (2008) found empirically that supplier-side risk sources are associated with measurable performance losses. Simchi-Levi, Schmidt and Wei (2014) introduced the risk exposure index, which estimates the impact of a node failure regardless of its probability, a concept that informs the exposure multiplier used here.

The early-warning literature in macroeconomics offers a well-tested method for selecting leading indicators. Kaminsky, Lizondo and Reinhart (1998) proposed the signals approach, in which each indicator issues a signal when it crosses a threshold, and indicators are ranked by their noise-to-signal ratio: the share of false signals in tranquil periods divided by the share of correct signals in pre-crisis windows. In the supply chain domain, the Federal Reserve Bank of New York's Global Supply Chain Pressure Index (Benigno *et al*., 2022) demonstrated that a composite of transportation costs and manufacturing survey components can track systemic supply stress. Such indices are valuable context but operate at a macro level; they cannot tell a plant which supplier of which part is about to fail.

Chen, Chiang and Storey (2012) described the evolution of BI and analytics from reporting toward predictive and prescriptive use. Baryannis *et al*. (2019) reviewed artificial intelligence in SCRM and noted that most work concentrates on risk identification and assessment, with less attention to interpretability and integration with decision processes. Ivanov (2020) used simulation to show how the timing of facility closures and recovery shapes disruption impact, underscoring the value of early detection. Supplier financial distress models, from Altman's (1968) Z-score onward, provide one well-established family of leading signals.

Even so, few frameworks address supplier-and-part-level early warning in heavy electrical equipment manufacturing, where lead times are long, sources are concentrated and customer commitments are rigid. Practitioner BI dashboards typically display many metrics without a principled method for deciding which ones lead disruption, and risk scores are often disconnected from pre-agreed actions, so an alert produces discussion rather than mitigation.

This paper therefore examines how a power-systems manufacturer can design a BI-driven early-warning system that detects supply disruption risk early enough to act, with a false-alarm rate that procurement and operations teams can sustain. It specifies a leading-indicator design procedure that qualifies BI signals by measured lead time and noise-to-signal ratio, develops a transparent risk-scoring framework that separates disruption likelihood from business exposure and maps scores to a tiered mitigation playbook, and grounds both in practitioner experience proactively identifying disruptions and building mitigation strategies to protect continuity of supply. The behavior of the framework is illustrated with a backtest on a synthetic supplier panel whose structure reflects practitioner-reported conditions; the results demonstrate design trade-offs rather than field performance.

The remainder of the paper is organized as follows. Section 1.1 reviews related research and derives the design implications adopted by the framework. Section 2 describes the research method, including the design of the leading indicators, the risk-scoring framework, the BI implementation and the synthetic backtest. Section 3 presents and discusses the illustrative results, and Section 4 concludes.

1.1. Related Research and Design Implications for Supplier-Level Early Warning

Five literatures bear directly on the design problem set out above: how supplier assessment criteria become monitored risk signals, how early-warning models score those signals, whether the underlying BI data are visible and trustworthy enough to act on, how disruption risk and resilience are conceptualized, and who owns the response once an alert is raised. Content-analysis and state-of-the-art reviews show that supply chain risk management research is extensive but concentrates on identification and assessment rather than on monitoring routines tied to decisions (Emrouznejad *et al*., 2023; Baryannis *et al*., 2019). The subsections below therefore read each stream for the specific design choice it informs in the proposed early-warning system and identify the requirement (R1 to R4, Section 2.1) that it supports.

1.1.1. Supplier assessment criteria as monitored risk signals

Supplier selection research supplies most of the criteria that an early-warning system later monitors. Strategic selection models weigh cost, quality, delivery and capacity (Sarkis & Talluri, 2002; Vonderembse & Tracey, 1999), and later work adds ecosystem and risk criteria to performance measures (Viswanadham & Samvedi, 2013) or builds supplier risk impacts directly into the selection model (Straube *et al*., 2016). In engineering, procurement and construction supply chains, Micheli *et al*. (2008) contrasted managing supply risk through supplier selection with managing it through ongoing supply risk management, a distinction that matters here because selection fixes the supplier base while early warning must operate on that base afterward. Joint lot-size, supplier and carrier decisions (Choudhary & Shankar, 2013), multiple-sourcing allocations designed proactively against risk (Ghamari, 2020) and closed-loop network designs that include supplier selection (Ghassemi *et al*., 2018) show that order allocation itself creates the exposure that the multiplier E(i) later scores.

Several streams explain why selection-time assessments age. Buyer and supplier power shifts over the life of a relationship

(Cox, 2001), supplier economies of scale shape which suppliers are chosen in the first place (Badorf *et al*., 2019), and supplier-buyer risk in raw-material procurement evolves with market conditions (Handayani, 2018). Tender evaluation methods in public procurement (Bergman & Lundberg, 2013), Kraljic-matrix green procurement screens (Garzon *et al*., 2019), fuzzy evaluation with smart and sustainable criteria (Demiralay & Paksoy, 2022), intuitionistic fuzzy AHP for e-procurement (Deepika, 2023) and enablers of green supplier selection (Gong *et al*., 2024) each produce a point-in-time ranking, and optimization models for emergency procurement in energy supply (Noh & Hwang, 2023) address what to buy once a shortage has already occurred. The proposed system instead re-scores every supplier-part pair weekly, so that the selection rationale is tested continuously against transactional evidence, which is the purpose of requirement R1.

Digital procurement narrows the gap between selection and monitoring. E-procurement and supply chain innovation are associated with the supply chain performance of manufacturers (Ibrahim *et al*., 2023), information sharing acts through supplier quality management and agility (Setyawan Firmansyah & Siagian, 2022), and the digital transformation of procurement is increasingly framed as a supply chain risk question (Mizgier, 2024). Artificial intelligence frameworks for supplier selection and performance monitoring (Mohammed, 2023) and hybrid multi-criteria and machine learning approaches that keep supplier selection explainable (Abdulla & Baryannis, 2024) point toward continuous supplier scoring, while aerospace experience shows that supplier risk mitigation needs a structured methodology rather than ad hoc review (Raj Sinha *et al*., 2004). The design implication is that the supplier drill-down view (Section 2.8) must display which indicators drive a score, so that an alert remains as explainable as the selection decision that created the exposure.

1.1.2. Early-Warning Models and Supplier Risk Scoring

Early-warning systems have been proposed at several levels of the supply chain. Genc *et al*. (2014) designed an event-based supply chain early-warning system that feeds adaptive production control, and Fu *et al*. (2012) combined fuzzy risk measurement with early warning for project material supply. Nagy and Foltin (2022) argued that early-warning signals extracted through big-data analysis can increase supply chain resilience, and Wang (2024) proposed a multimodal deep learning approach that combines natural language processing with anomaly detection, which corresponds to the news-sentiment indicator in Table 1. Financial early-warning models apply particle swarm optimization to supply chain default risk (Yin & Li, 2022) and convolutional neural networks to supply chain financial risk (Computational Intelligence and Neuroscience, 2023), although the latter article carries a retraction notice, as does a pollution-risk early-warning model for an urban drinking water supply chain (Cao *et al*., 2022). These retractions strengthen the case for transparent, auditable indicator qualification over opaque model output.

At the supplier level, Steinberg *et al*. (2023) used machine learning to predict late supplier deliveries of low-volume, high-variety products in the German machinery industry, a setting close to power-systems equipment and a target close to the OTD indicator used here. Risk indices aggregate several criteria into one number, as in a supply chain risk assessment index for small and medium enterprises after COVID-19 (Babu & Yadav, 2023), a grey multi-objective binary linear programming model for risk assessment (Vafadarnikjoo *et al*., 2023), structural modeling for classifying and prioritizing disruption risks (Alora & Barua, 2019), formal models of disruption risk within supply chain risk management (Bilsel & Ravindran, 2012) and a data-fusion index of cyber resilience for additive manufacturing supply chains (Rahman *et al*., 2021). Predictive risk analytics for enterprise technology estates (Okwesa *et al*., 2024) adds a lesson about data pipelines: an alert must distinguish an abnormal supplier signal from one created by stale, missing or inconsistent system data. Two design choices follow. Indicators enter the composite only after lead-time and noise-to-signal qualification (R1), and the composite is reported as a risk propensity index rather than a probability until calibration is shown (Section 2.5).

1.1.3 Visibility, Information Sharing and Bi Data Quality

Visibility determines whether the indicators in Table 1 can be observed at all. Francis (2008) showed that supply chain visibility is defined inconsistently, Messina *et al*. (2022) proposed a model for assessing how visible a supply chain actually is, and Goswami *et al*. (2013) compared information visibility in two supply chain management information systems. Interorganizational information systems visibility is associated with supply chain performance (Lee *et al*., 2014), and the impact of increased visibility has been evaluated quantitatively (Baycik, 2024). Supply chain digitalization improves performance through visibility and survivability (Al Tera *et al*., 2024), and information integration supports innovativeness and resilience among manufacturing firms (Muhwezi *et al*., 2023). For this framework, visibility means that each indicator has a defined source, refresh interval and availability timestamp, so that only information available on the scoring date enters the score.

Information sharing research explains what suppliers are willing to provide and who benefits. Early studies related information sharing and ordering coordination to performance (Zhao *et al*., 2002) and estimated the value of shared information for inventory management (Cachon & Fisher, 2000). Design, integration and information sharing have distinct effects on performance (Sezen, 2008), integration enhances sharing (Koçoğlu *et al*., 2011), and sharing works together with visibility, agility and collaboration (Baah *et al*., 2021). Backward sharing benefits some partners more than others (Han *et al*., 2021), interdependence shapes sharing in the extended supply chain (Kembro & Selviaridis, 2015), and agency theory can guide incentives for sharing (Manatsa & McLaren, 2008). Studies of internal sharing during an innovation project (Ruel *et al*., 2013), visibility and resource sharing among humanitarian practitioners (Maghsoudi & Pazirandeh, 2016), system dynamics models of sharing (Feng, 2012), RFID-enabled sharing moderated by supply chain culture (Kim *et al*., 2015), interoperability in a circular economy (Khan & Abonyi, 2022) and frameworks for sharing risk information among partners (Ahmed *et al*., 2023) indicate that upstream data are negotiated rather than given. Work linking sharing to resilience through artificial intelligence and collaboration (Ali *et al*., 2024), to sustainable performance through digital supply chains (Le *et al*., 2024) and to sustainability in small firms (Mehmood *et al*., 2024, an article since retracted) points the same way. Accordingly, the framework relies first on

signals the manufacturer already owns, such as acknowledgment delay and lead-time drift, and treats supplier-shared capacity data as an enhancement (Section 3.6).

Information quality affects performance through information sharing (Kankam *et al*., 2023), and IT advancement and assimilation build supply chain capabilities (Tigga *et al*., 2021). Big data analytics creates both opportunities and challenges for supply chain management (Kache & Seuring, 2017), and a case study of managing supply chain data shows that data handling is itself a source of future risk (Hoeksema, 2019). These findings justify two features of the BI implementation: a data-quality flag that separates a supplier signal from a stale or missing feed, and an unscored status for suppliers whose indicators cannot be identified, so that missing evidence never produces a zero-risk classification.

1.1.4. Disruption Drivers, Propagation and Exposure

The disruption literature frames the risk that the composite score is meant to anticipate. Kleindorfer and Saad (2005) set out a framework for managing disruption risks, Konecka (2016) summarized the theoretical principles of managing supply chain disruption risk, and Friesz (2011) introduced a collection of analytical work on disruption and risk management. Grounding supply disruption risk in enactment theory (ELLIS *et al*., 2011) implies that managers can read the same signal differently unless thresholds are explicit. Empirical studies relate disruption risk drivers to organizational performance in Chinese supply chains (Parast & Subramanian, 2021) and among manufacturing firms in the CALABARZON region (Duay, 2023), link risk-taking propensity and security practices to disruption occurrence (Park *et al*., 2016), and examine how just-in-time practices affect disruption risk depending on supply chain centralization (Ye *et al*., 2022). Hamidu *et al*. (2023) examined the role of disruption in the relationship between resilience and performance in manufacturing firms. Together these studies support treating disruption as an observable event with a defined onset, which is how Section 2.4 operationalizes it.

Exposure depends on network position as well as on the supplier's own condition. Disruptions propagate as systemic risk through tightly coupled networks (Scheibe & Blackhurst, 2018), network behavior under disruption risk evolves over time and space (Wang *et al*., 2022b), and multi-echelon disruption threatens customer service levels in ways that single-node views miss (Schmitt, 2011). Network design models incorporate disruption risk in global supply chains (Rienkhemaniyom & Ravindran, 2014), in bi-objective green networks (Wang *et al*., 2022), in resilient networks under ambiguous information (Chen & Chen, 2023) and in straw supply chains facing facility disruption (Mao *et al*., 2024), while Li and Ru (2014) proposed a disruption risk defense system and Yang *et al*. (2023) modeled logistics alliance decisions under disruption risk as an evolutionary game. Simchi-Levi *et al*. (2015) identified risks and mitigated disruptions in the automotive supply chain using exposure-based analysis, and Wildgoose *et al*. (2012) argued that reducing disruption risk starts with understanding one's own supply chain. The exposure multiplier in Equation (6) is a deliberately simple, part-level proxy for these network effects: criticality, sourcing concentration and inventory vulnerability can be read from the bill of materials, sourcing records and inventory data that the BI environment already holds (R2).

Disruption costs extend beyond lost production. Reputational risk must be managed with logistics providers during disruption recovery (Blom & Niemann, 2022), reverse logistics risk rises during recovery in omni-channel fashion retail (Ermes & Niemann, 2023), and pricing policy for green products must adapt under supply disruption (Chatterjee *et al*., 2024). Disruption orientation is linked to resilience and market performance (Stephens *et al*., 2022) and, through risk management practices and analytics capability, to resilience (Liu & Wei, 2022). The COVID-19 pandemic produced a catalogue of disruption management strategies (Moosavi *et al*., 2022), and additive manufacturing has been examined as a route to reshoring and shorter supply chains (Calignano & Mercurio, 2023). For a power-systems manufacturer whose utility customers hold firm in-service dates, these findings support scoring criticality c(i) by contractual penalties and customer commitments rather than by part cost alone.

1.1.5. Resilience Capabilities and The Timing of Mitigation

Mitigation research establishes that the value of a warning depends on the response options available when it arrives. Tomlin (2006) showed that the preferred mix of mitigation and contingency strategies depends on supplier reliability and on the capacity and speed of backup supply, and He *et al*. (2019) valued disruption mitigation as a real option. Flexibility-driven strategies differ in how well they mitigate supply disruption (Carbonara & Pellegrino, 2017), supply chain finance strategies address both disruption and commodity price volatility risks (Pellegrino, 2024), and resource sharing can serve as a disruption risk management measure (Cockx *et al*., 2019). Firm resilience to supply chain disruptions has been measured with a validated scale (Ambulkar *et al*., 2015), performance measurement during disruption has been studied (Saleheen & Habib, 2023), and resilience has been evaluated in relation to supply chain structure (Aguila & ElMaraghy, 2019). Section 3.4 applies this reasoning directly by comparing the response times of the actions in Table 2 with the indicator leads in Table 3.

Resilience capabilities determine how much warning a firm needs. Ambidexterity, agility and resource flexibility support resilience (Aslam *et al*., 2020; Jamaludin *et al*., 2023), entrepreneurial leadership improves performance through resilience (Haq & Aslam, 2023), and resilience orientation underpins sustainable performance in business-to-business firms (Rahman *et al*., 2023). Supply chain finance strengthens resilience from a dynamic capability perspective (Lu *et al*., 2024) and under disruption (Shahzad & Irfan, 2024). Studies of resilience enhancers in Kenyan manufacturing (ARANI, 2015), of managerial resilience strategies calibrated to anticipate global disruptions in export-oriented manufacturers (Liana, 2024), of the importance of resilience in an empirical investigation (Alfarsi *et al*., 2019), of agricultural biomass supply chains under COVID-19 and sustainability compliance (Zahraee *et al*., 2022) and of integration and resilience in new energy vehicle manufacturing (Zhang *et al*., 2024) show that the response repertoire differs by sector and firm. The framework therefore does not prescribe universal actions; it requires each firm to pre-approve its own tier actions and owners (R4).

Digital capabilities shorten detection and response. Digital supply chain twins support the management of disruption risks (Ivanov & Dolgui, 2021), digital technology and

Industry 4.0 affect the ripple effect and risk analytics (Ivanov *et al*., 2019), and investment constraints shape the roadmap to digital resilience (Al-Banna *et al*., 2023), as reviewed for the interplay of resilience, Industry 4.0 and investment (Al-Banna *et al*., 2023b). Digital twins influence sustainability through resilience (Singh *et al*., 2023), information processing and digital technology support resilience through risk management (Azizah *et al*., 2024), and big data analytic capability combines with integration and resilience to improve performance (Sari *et al*., 2023), while artificial intelligence has been characterized as either disruptive innovation or innovative disruption for supply chain management (Hendriksen, 2023). Distributed manufacturing platforms (Villar *et al*., 2024), international manufacturing strategy in semiconductors (Fleisch & von Dzengelevski, 2024), additive manufacturing for military logistics (Dymyt *et al*., 2024) and additive manufacturing supplier risk mitigation (Zerga, 2019) widen the set of alternate sources, but each carries a qualification lead time. Reviews of resilience in global distribution networks (Anene, 2021), of risk management culture (Akbar & Isfianadewi, 2023) and of building risk resilience (Singh & Singh, 2019), together with evidence on supply chain alertness and preparedness (Opoku, 2024), stress that detection is valuable only when coupled to prepared responses, which is the rationale for the playbook in Table 2.

1.1.6. Forecasting, Inventory and Planning Analytics

Forecasting research separates prediction accuracy from operational use. Key performance indicator models for demand forecasting incorporate supply chain reliability and seasonality (Tadayonrad & Ndiaye, 2023), hybrid models combine logistic regression with neural networks to improve supply chain indicators (Pietukhov *et al*., 2023), multi-phase hierarchical machine learning forecasts operate at several aggregation levels (Taghiyeh *et al*., 2023), and ensemble deep learning forecasts feed order-up-to inventory policies (Seyedan *et al*., 2023). Predictive analytics can improve demand forecasting accuracy and reduce inventory inefficiencies (Aifuwa *et al*., 2020), analytics frameworks target forecasting accuracy and bottlenecks (Akin-Oluyomi & Akhigbe, 2023), and top management support conditions the value of big data predictive analytics (Shafique *et al*., 2024). Reviews cover similarity-matching in supply chain analytics decisions (Herden, 2017) and analytics for targeted advertising in e-commerce (Pundir *et al*., 2024), showing how widely the analytics toolkit has spread beyond supply risk. Forecast sharing mitigates bias magnification (Sanders & Graman, 2016) and shapes cooperative pricing between a manufacturer and an e-retailer (Yan & Ghose, 2008), and behavioral regularities affect inventory and forecasting decisions (Manousiadou, 2024). The framework adopts the separation between accuracy and usefulness: Section 3.2 reports recall and precision, but usefulness is judged by warning time relative to mitigation time.

Inventory and capacity models explain why the same signal carries different risk for different parts. Variable lead time and random supplier capacity change optimal inventory (Wu, 2001), job mix and capacity bottlenecks affect inventory and due-date performance (HUQ & BERNARDO, 1995), and demand planning, inventory and capacity planning interact in semiconductor supply chains (Uzsoy *et al*., 2018). Replenishment under an (R, s, S) policy (Žic *et al*., 2023), inventory systems for deteriorating items (Chandramohan *et al*., 2023) and models with dynamic lead time under carbon reduction and uncertain demand (Karthick & Uthayakumar, 2022) all make lead time and coverage central variables. Early supplier involvement reduces lead time through the information supply chain (Hanson, 2018), and postponed manufacturing can absorb demand uncertainty (van Hoek, 1997). These results motivate the inventory vulnerability factor v(i), the ratio of replacement lead time to weeks of coverage, which raises exposure when cover is thin relative to the time replacement would take.

Planning studies add the product-transition problem. Supplier integration into new product development coordinates product, process and supply chain design (Petersen *et al*., 2005), and supply chain readiness for a new product must be created during development (Tolonen *et al*., 2017). Data-driven risk mitigation can be integrated into supply chain planning (Gillespie, 2023). For power-systems equipment, where engineering changes and new ratings regularly introduce new parts and suppliers, these studies imply that new supplier-part pairs need commodity-group baselines until their own history is long enough for normalization (Section 2.3), and that alerts on parts for products in transition should be reviewed jointly by procurement and engineering.

1.1.7. Decision Behavior and The Case for Pre-Agreed Responses

Behavioral research explains why alerts often produce discussion rather than action. Purchasing managers perceive bias in supplier-selected referrals (Hada *et al*., 2013), dual-sourcing bias distorts responsible sourcing decisions (Mahmoudzadeh & Chaturvedi, 2024), and sustainable supply chain decisions in non-exemplar firms follow behavioral rather than purely economic logic (Kirchoff *et al*., 2015). The behavioral agency model links managerial risk bearing to operations and supply chain decisions (Gomez-Mejia *et al*., 2021). Much of this evidence comes from laboratory experiments, whose rigor and usefulness in supply chain research have been debated (BACHRACH & BENDOLY, 2011; SIEMSEN, 2011; Knemeyer & Naylor, 2011), and from classroom games and negotiation exercises on sourcing and coordination (Fawcett & McCarter, 2006; Gumus & Love, 2012; Inouye & Kling, 2020), while dyadic survey research faces its own nonresponse bias (Clottey & Benton, 2020). Negotiation has also been automated through agent-based protocols for supply chain formation (Wang *et al*., 2009; Kim & Cho, 2010) and supply chain finance (Fiedler, 2022), and collaborative decision models support reverse logistics in an automobile network (Hernández *et al*., 2010).

Two implications follow for the early-warning system. First, because buyers interpret ambiguous signals through their own incentives and heuristics, the escalation threshold must be fixed in advance and the score must show its drivers. Second, collaboration strategies require explicit implementation choices (Malviya *et al*., 2024) and relational capital (Saleh & Roslin, 2015), and collaboration is itself a governance arrangement (Jain & Dubey, 2005). Requirement R4 therefore binds each tier to a pre-approved action set and a named owner, so that the decision to act is taken once, deliberately and before any specific supplier is under stress, rather than renegotiated at each alert.

1.1.8. Governance, Integration and Measurement of The Response

Governance research specifies who controls a response and on what evidence. Supply chain governance has been defined as a distinct management problem (Diaz, 2006), governs value creation in supply chain relationships (Hammervoll, 2011) and influences supply chain performance (Dolci *et al*., 2017). Governance mechanisms perform differently across supply networks of varying complexity (Tachizawa & Wong, 2015), and additive manufacturing reshapes governance in the apparel supply chain (Hohn & Durach, 2021). Worker-driven governance (Reinecke & Donaghey, 2020) and the contribution of non-commercial organizations (Shirgholami *et al*., 2024) show that governance can extend beyond buyer and supplier. Traceability supports transaction governance (Vo *et al*., 2016), digital governance integrates transparency, traceability and risk management (Omitoyin *et al*., 2024), agile digital transformation can embed IT risk and ISO compliance controls (Mbonu *et al*., 2020), and force majeure clauses define contractual resilience in energy supply chains (Uchechi *et al*., 2020). For a power-systems manufacturer, a substitute part approved under an Action-tier alert still requires engineering and quality sign-off, so the playbook assigns engineering approval explicitly (Table 2).

Supplier relationship management fosters collaboration and resilience across organizational boundaries (Ike *et al*., 2021), collaborative supply risk mitigation depends on the buyer-supplier relationship (Mwesiumo *et al*., 2021), and strategic supplier relationship management can improve risk mitigation in maritime supply chains (Vaandrager, 2024). Supplier sustainability risk may be mitigated, avoided or accepted (Hajmohammad & Vachon, 2015), a typology that maps onto the choice between acting on an alert, exiting a supplier and documenting an accepted risk. Security threats in ICT product supply chains (Li *et al*., 2023) and information management in supply chain innovation (Zambujal-Oliveira, 2019) have been analyzed with game theory, and supply chain decisions in governmental organizations carry their own constraints (Ferrer *et al*., 2016). Disruptive technologies are expected to reshape future supply chains (Tavana, 2023), and decision models address barriers to green supply chain management (Özaşkın & Görener, 2023) and bilevel green supply chain design (Caramia & Stecca, 2024). These works support recording, for every alert, the action chosen, its owner and its outcome, which the action log in Section 2.8 provides.

Integration and performance research warns that local improvements can shift cost elsewhere. Supply chain integration affects the cost efficiency of contract manufacturing (Kim & Schoenherr, 2018), decision support improves flow management in a supply chain subject to risks (Hilali *et al*., 2024), and stochastic optimization supports integrated network design for advanced air mobility aircraft manufacturing (Dulia & Shihab, 2024). Agility contributes to supply chain fit (Gligor, 2016) and mediates the link between supply chain orientation and performance (Dhaigude & Kapoor, 2017); lean, agile, resilient and green paradigms interact in sustainable performance (Anvari, 2021); and management strategy and practices (Sukati *et al*., 2012), supplier performance with transformational leadership (Purwanto & Juliana, 2022) and operational practices among early adopters of green supply chain management (Zhu & Sarkis, 2004) all shape measured performance. Lean has fragmented as a management concept (Schonberger, 2019), and combining business process management with lean improves information and documentation flows (Calçado *et al*., 2024). Life-cycle costing in the food packaging supply chain (James, 2003) shows that costs incurred at one stage are often borne at another. In this framework the analogous shift is between procurement time spent on false alerts and production losses from missed disruptions, which is why Table 4 reports false alarms per 100 supplier-weeks alongside recall and precision.

2. Research Method

2.1 Research Design

The study combines design-oriented model building with a simulation-based illustration. Design requirements were derived from the literature reviewed in Section 1.1 and from practitioner experience, and the framework was then specified to meet them. The specification follows the established sequence of supply chain risk management, in which risks are identified, assessed, mitigated and monitored (Chopra & Sodhi, 2004; Tang, 2006), but places its emphasis on monitoring, the stage that the literature treats least formally. Because firm-level disruption records are proprietary, the behavior of the framework is examined on a synthetic supplier panel whose structure reflects practitioner-reported conditions in power-systems manufacturing (Section 2.9). The synthetic results illustrate design trade-offs; they are not estimates of field performance.

The practitioner evidence comes from the first author's work in power-systems manufacturing supply chain management, where the core responsibility was to identify supply chain disruptions proactively and to develop mitigation strategies that protect continuity of supply. Four lessons from that work shaped the design. Delivery performance proved to be a late signal, which is why research on late supplier deliveries seeks to predict them before they occur (Steinberg *et al*., 2023): on-time delivery (OTD) deteriorates only after a supplier's problem is already affecting shipments, while earlier signs typically appeared upstream as quoted lead times creeping outward on new requests for quotation, slower acknowledgment of purchase orders, partial-quantity confirmations and requests to change terms. External context mattered only when tied to exposure; commodity spikes in electrical steel, copper and aluminum, or freight disruptions on specific lanes, were relevant only for the suppliers and parts exposed to them, and undifferentiated market news created alert fatigue. The value of a warning depended on the mitigation lead time, since a warning is useful only if it arrives earlier than the time needed to qualify an alternate source, place a bridge buy or re-sequence a build, so indicators must be judged in weeks of lead rather than by correlation alone. Finally, mitigation moved fastest when procurement, engineering, quality and operations had agreed in advance which actions each risk level would trigger and who owned them.

These observations translate into four design requirements: (R1) indicators must be qualified by measured lead time against disruption events; (R2) likelihood must be separated from exposure; (R3) alert levels must be calibrated to an acceptable false-alarm workload; and (R4) each alert level must map to an owned, pre-approved mitigation action.

The early-warning system has five layers: (1) signal acquisition from BI sources, (2) normalization, (3) leading-indicator qualification, (4) composite likelihood scoring with an exposure multiplier, and (5) tiered alerting linked to a

mitigation playbook. The unit of analysis is the supplier-part pair *i* observed weekly at time *t*.

2.2. Signal Architecture

Table 1 lists the candidate indicators. They are grouped into internal transactional signals, which the manufacturer controls and observes directly, and external context signals, which are licensed or public. All are typically available within an existing BI stack through ERP extracts, supplier portal logs and third-party data feeds. The internal signals follow the practitioner observation that supplier stress appears first in quoting and order-confirmation behavior: lead-time drift reflects capacity committed elsewhere in the supplier's order book, consistent with the central role of lead time in supplier involvement (Hanson, 2018), while acknowledgment delay and partial confirmations reveal allocation decisions before any shipment is late. The financial health composite draws on the ratio-based tradition of bankruptcy prediction (Altman, 1968), whose deterioration can precede operational failure by months. Commodity and freight indices translate macro pressure of the kind summarized by the Global Supply Chain Pressure Index (Benigno *et al*., 2022) into supplier-specific exposure, and the commodity group captures the price-volatility risk that supply chain strategies seek to mitigate (Pellegrino, 2024). News sentiment corresponds to text-based anomaly detection (Wang, 2024). Every indicator carries an availability timestamp, so a value enters the score only after the date on which it could actually have been observed.

Table 1: Candidate leading indicators and BI data sources

Indicator	Definition (weekly, per supplier-part)	Typical BI source	Expected direction
OTD decline	Rolling 4-week on-time-in-full rate versus 26-week baseline	ERP receipts vs. promise dates	Falls before disruption
Lead-time drift	Change in quoted or confirmed lead time on new POs and RFQs	ERP, sourcing tool	Rises before disruption
PO acknowledgment delay	Days from PO issue to supplier confirmation; share of partial confirmations	Supplier portal, EDI 855	Rises before disruption
Financial health	Composite of credit score change, payment behavior and Z-score proxy	Credit-risk data provider	Deteriorates before disruption
Commodity index	Price and volatility of exposed inputs (e.g., electrical steel, copper, aluminum, resin)	Market data feed	Spikes before disruption
Freight index	Lane-specific cost and transit-time variance	Logistics provider, freight indices	Rises before disruption
News sentiment	Count and tone of adverse events (labor, fire, sanctions, weather) mapped to supplier sites	News or event-monitoring service	Worsens before disruption

Note: EDI 855 is the electronic purchase order acknowledgment transaction. Indicators are signed so that higher values indicate higher risk.

2.3. Normalization

Because suppliers differ in scale and historical volatility, each raw indicator *x* is converted to a robust z-score relative to that supplier-part's own history, using the median and the median absolute deviation (MAD):

$$z(i,k,t) = \frac{x(i,k,t) - \text{median}(x(i,k,\tau), \tau < t)}{1.4826 \times \text{MAD}(x(i,k,\tau), \tau < t)} \quad (1)$$

The median and MAD are used instead of the mean and standard deviation because a supplier's own disruption episodes produce extreme values that would otherwise inflate the scale and mask the next episode; the constant 1.4826 makes the MAD comparable with a standard deviation when the data are approximately normal. Normalizing against each pair's own history mirrors the signals approach, in which thresholds are set relative to each country's own indicator distribution rather than at a common absolute level (Kaminsky *et al*., 1998). The baseline uses a prespecified historical or rolling window ending before the scoring date, so future observations never enter it. Where the MAD is zero, as for a supplier whose acknowledgment time has never varied, an explicit positive scale floor or a documented fallback is applied and tested for sensitivity. New supplier-part pairs without sufficient history use commodity-group baselines, frozen within each evaluation fold.

2.4. Leading-Indicator Qualification

A disruption event is defined operationally as the first week in which a supplier-part pair causes a shortage that delays a scheduled production order, after at least eight preceding weeks without such a shortage. Events are drawn from shortage logs and production schedule variance reports.

Each candidate indicator is then evaluated on two criteria. The lead time is the lag, in weeks, at which the cross-correlation between the indicator and the disruption series is maximized. The noise-to-signal ratio (NTS), following Kaminsky *et al*. (1998), is computed with a signaling threshold $z > 1.5$ and a pre-event window of eight weeks:

$$\text{NTS}(k) = \frac{B/(B+D)}{A/(A+C)} \quad (2)$$

All contingency cells use a common supplier-week unit. Let *Y* equal one when a disruption begins within the next eight weeks and *S* equal one when the indicator crosses its threshold; *A* counts weeks with $S = 1$ and $Y = 1$, *B* counts $S = 1$ and $Y = 0$, *C* counts $S = 0$ and $Y = 1$, and *D* counts $S = 0$ and $Y = 0$. Weeks without a complete eight-week outcome horizon are excluded. The numerator of Equation (2) is the false-signal rate in tranquil weeks and the denominator is the hit rate in pre-event weeks, so an NTS below one means that the indicator signals more often before disruptions than at other times. An indicator is not identifiable when either outcome class has no observations, and a numerical floor cannot repair an absent class; such an indicator is excluded, and a supplier with no remaining eligible indicators is labeled unscored and referred for manual review rather than assigned zero risk. Qualification requires an NTS below one and a useful warning time at least as long as the response time of the relevant mitigation action. Cross-correlation identifies the typical lead but does not by itself establish predictive validity, and event-level detection is evaluated separately in Section 3.2.

2.5. Composite Likelihood Score

Qualified indicators are combined with weights inversely proportional to their noise-to-signal ratio, so that more reliable indicators carry more influence; this extends the ranking of indicators by noise-to-signal ratio in the signals approach (Kaminsky *et al*., 1998) from selection to weighting:

$$w(k) = \frac{1/\max(\mathrm{NTS}(k), \eta)}{\sum_j 1/\max(\mathrm{NTS}(j), \eta)}, \quad \eta > 0 \qquad (3)$$

$$L(i,t) = \frac{100}{1+\exp[-\alpha(\sum_k w(k)\, z(i,k,t) - \beta)]} \qquad (4)$$

The logistic transform maps the weighted standardized signal onto a 0-to-100 risk propensity index. It is not a calibrated disruption probability: the index rises monotonically with the evidence of stress, but the share of pairs at a given index value that actually experience a disruption must be estimated separately. Setting β = 1 gives an index of 50 at a weighted standardized signal of one, and α controls steepness. The positive NTS floor η prevents infinite weights and is prespecified with sensitivity analysis. Weights, thresholds and scale parameters are estimated on training periods only. Equation (4) has the functional form of logistic regression, which hybrid forecasting models in supply chains already use (Pietukhov *et al*., 2023); replacing the fixed weights with fitted coefficients is therefore a natural extension, but it would still require temporal validation and probability calibration before scores could be read as probabilities.

2.6. Exposure Multiplier

Following the distinction between likelihood and impact (Simchi-Levi *et al*., 2014), and requirement R2, the final risk score scales likelihood by business exposure:

$$R(i,t) = L(i,t) \times E(i) \qquad (5)$$

$$E(i) = 0.5 + 0.5 \times \frac{c(i)+s(i)+v(i)}{3} \qquad (6)$$

Each exposure factor is scored from 0 to 1. Criticality c reflects whether the part is on the bill of materials for constrained, high-margin or contractually penalized products (for example, a utility transformer with liquidated damages). Sourcing concentration s is 1 for single-source parts, 0.5 for dual-source parts with limited qualified capacity, and 0 for parts with readily qualified alternates. For positive replacement lead time, inventory vulnerability is v = min(1, lead time / max(weeks of coverage, δ)), using a small positive numerical floor δ and the same time units. Zero coverage with positive lead time gives v = 1; zero replacement lead time gives v = 0. Missing inputs require an unscored status and manual review. The multiplier ranges from 0.5 to 1.0, so a highly exposed part is escalated at a lower risk-index value than a non-critical, multi-source part.

2.7. Alert Tiers and The Mitigation Playbook

Scores are mapped to three alert tiers. To suppress one-week noise, an alert is raised only when the score exceeds the tier threshold for two consecutive weeks. The confirmation rule has a cost, because it consumes one week of warning; the first actionable alert, not the first threshold crossing, is therefore the point from which useful warning time is measured. Each tier is tied to a pre-approved set of actions with named owners (requirement R4), as shown in Table 2. Response windows shorten as the tier rises because the actions differ in cost and reversibility: confirming signals with a supplier costs little, whereas spot purchases and engineering approval of substitutes commit money and engineering capacity. This ordering reflects the distinction between mitigation actions taken in advance and contingency actions taken once a disruption is under way (Tomlin, 2006).

Table 2: Alert tiers, thresholds and mitigation playbook

Tier	Score R	Response window	Pre-approved actions	Owner
Watch	50 to 64	Review within 1 week	Confirm signals with supplier; verify open PO promise dates; check inventory coverage; flag in S&OP review	Category buyer
Alert	65 to 79	Act within 72 hours	Supplier risk call and recovery plan; increase safety stock or pull forward buys; initiate alternate-source qualification; notify planning	Supply chain manager
Action	80 and above	Act within 24 hours	Cross-functional response team; bridge buys or spot purchases; engineering approval of substitutes; production re-sequencing; customer communication where commitments are at risk	Director, supply chain and operations

Thresholds are set by explicit agreement on acceptable workload: managers decide how many false alerts per period they are willing to investigate in exchange for earlier warning (requirement R3). The thresholds in Table 2 (50, 65 and 80) are illustrative starting values that a firm would revise from its own action log. Section 3.2 illustrates the resulting trade-off.

2.8. BI Implementation

The framework is designed to run within an existing BI environment. A weekly extract-transform-load job pulls ERP purchase order and receipt tables, supplier portal acknowledgment logs and third-party feeds into a supplier-part fact table. Normalization and scoring run as scheduled SQL or Python transformations. The BI layer presents three views: a portfolio heat map of all supplier-part pairs by tier, a supplier drill-down showing which indicators drive the score, and an action log recording who responded, what was done and whether a disruption followed. The load job also records the refresh time of every feed, and the drill-down flags any score that rests on a stale, missing or inconsistent input, so that a reviewer can tell a supplier problem from a data problem (Hoeksema, 2019). This design follows the progression of BI from descriptive reporting toward predictive and prescriptive use (Chen *et al*., 2012). The action log closes the loop, supplying labeled outcomes for quarterly recalibration of thresholds and weights.

2.9. Design of the synthetic backtest

The synthetic panel contains 80 supplier-part pairs observed weekly over 156 weeks, or 12,480 supplier-weeks. In the generator, a latent stress process for each pair is perturbed by random shocks, disruptions arise from elevated stress, and each of the seven indicators reflects that stress with its own lead and noise level; the generator produced 108 disruption events under the definition in Section 2.4. This use of simulation follows studies of how the timing of disruption and recovery shapes impact (Ivanov, 2020), but the parameters reflect practitioner-reported conditions rather than estimates from firm records. All results in Section 3 are therefore synthetic and illustrative: they show how the framework's thresholds trade detection against workload, not how it would perform at a specific manufacturer, and they should not be read as out-of-sample estimates. A field evaluation would separate training and testing in time, fitting normalization, weights and thresholds on training periods only, with a purge interval covering the eight-week prediction horizon. It would also group persistent signals into alarm episodes, keep event-level hit rates distinct from supplier-week contingency measures, and estimate uncertainty with methods that account for repeated supplier observations and overlapping outcome windows.

3. Results and Discussion

3.1. Indicator Qualification Results

Table 3 reports the illustrative lead times, NTS values and weights obtained on the synthetic panel. All seven NTS values are below one, so every indicator signals more often before disruptions than in tranquil weeks, which is the first qualification criterion of the signals approach (Kaminsky *et al*., 1998). Lead-time drift has the lowest NTS (0.15), the highest pre-event hit rate (0.44) and therefore the largest weight (0.192), while news sentiment has the highest NTS (0.24) and the smallest weight (0.118). Peak leads range from two weeks for OTD decline to eight weeks for financial health, matching the practitioner ordering in Section 2.1: delivery performance moves last, and balance-sheet stress of the kind captured by Z-score-type ratios (Altman, 1968) moves first. Peak cross-correlations are low (0.17 to 0.26), as expected for rare events, which is why qualification relies on NTS rather than correlation. Full qualification also depends on the response time of the relevant mitigation: a two-week OTD lead can support a bridge buy but cannot qualify a months-long alternate-source action (Section 3.4). The values demonstrate the intended weighting logic, not empirical indicator quality.

Table 3: Leading-indicator qualification (synthetic panel)

Indicator	Peak lead (weeks)	Peak cross-correlation	NTS ratio	Hit rate in pre-event window	Composite weight
OTD decline	2	0.26	0.22	0.35	0.129
Lead-time drift	5	0.24	0.15	0.44	0.192
PO acknowledgment delay	4	0.22	0.18	0.38	0.162
Financial health	8	0.18	0.22	0.30	0.130
Commodity index	6	0.19	0.19	0.33	0.147
Freight index	3	0.19	0.23	0.31	0.121
News sentiment	7	0.17	0.24	0.27	0.118

Note: Synthetic panel. NTS computed with threshold $z > 1.5$ and an 8-week pre-event window. Hit rate is the share of pre-event weeks in which the indicator signaled. Weights are inverse-NTS normalized and sum to 1; they were computed from unrounded NTS values and may differ slightly from weights recomputed from the rounded ratios shown.

3.2. Early-Warning Performance

Table 4 compares, on the synthetic panel, the composite score at each tier threshold with two single-indicator monitors and an equal-weighted composite. An alarm counts as a correct warning if a disruption for the same supplier-part pair follows within 12 weeks; this evaluation window is wider than the eight-week qualification window so that indicators with the longest leads, such as financial health, are not penalized for early signals. Recall is the share of disruptions preceded by at least one alarm, precision is the share of alarms followed by a disruption, and median warning is the number of weeks between the first confirmed alarm and the disruption. Precision and the false-alarm rate per 100 supplier-weeks are reported alongside recall because the signals approach treats false signals in tranquil periods as a cost of equal standing with missed crises (Kaminsky *et al*., 1998).

Table 4: Backtest performance on the synthetic panel (108 events, 80 supplier-part pairs, 156 weeks)

Monitor	Recall	Precision	Median warning (weeks)	Total alarms	False alarms per 100 supplier-weeks
OTD only ($z > 1.5$)	0.82	0.44	2	216	0.96
Lead-time drift only ($z > 1.5$)	0.76	0.43	5	210	0.95
Equal-weight composite	0.82	0.31	6	320	1.77
Composite, Watch ($R \geq 50$)	0.82	0.31	6	314	1.75
Composite, Alert ($R \geq 65$)	0.74	0.41	5	207	0.98
Composite, Action ($R \geq 80$)	0.60	0.59	5	115	0.38

Note: Synthetic panel. The exposure multiplier is set to 1.0 for all pairs in this illustration so that tiers reflect likelihood only. Alarms require two consecutive weeks above threshold.

Three patterns stand out in these illustrative results. First, the composite at the Watch tier detects the same share of disruptions as OTD monitoring (82 percent) but does so with a median of six weeks of warning rather than two. For a buyer, those additional weeks are often the difference between a planned bridge buy and an emergency expedite. Second, raising the threshold improves precision sharply, from 0.31 at Watch to 0.59 at Action, and cuts false alarms per 100 supplier-weeks by nearly 80 percent (from 1.75 to 0.38), at the cost of lower recall (from 0.82 to 0.60). This is the explicit workload trade-off described in Section 2.7, and it is why the tiers are tied to different response intensities rather than treated as a single binary alert. Third, inverse-NTS weighting performs about the same as equal weighting on this

panel, because the indicators were generated with similar quality. In real data, where indicator quality varies widely, the weighting step is expected to matter more, and the qualification procedure is what prevents weak indicators from entering the composite at all.

On its own, lead-time drift matches the composite's Alert tier on this panel (recall 0.76 versus 0.74, precision 0.43 versus 0.41, both with a five-week median warning). This is consistent with practitioner experience, although the synthetic design may favor it, and it has a practical implication: firms that cannot yet license external data could start by instrumenting lead-time drift and acknowledgment latency from their own ERP and supplier portal data, the two indicators with the largest weights in Table 3. The expected advantage of the composite lies less in average accuracy than in breadth, since it remains informative when a supplier's quoting behavior is stable but its finances or input markets deteriorate. Testing that expectation requires real supplier data, of the kind already used to predict late supplier deliveries in machinery manufacturing (Steinberg *et al*., 2023).

3.3. From Dashboards to Decisions

The central design choice is to treat early warning as a decision system rather than a reporting system. Many BI deployments in procurement already display delivery metrics, spend and supplier scorecards. The framework adds three things those dashboards usually lack: evidence about which metrics lead disruption and by how much, a single score that separates likelihood from exposure, and a mapping from score to owned action. This reflects the practitioner lesson that mitigation moves fastest when actions are agreed before the alert arrives. It also responds to the observation that artificial intelligence research in supply chain risk management gives less attention to interpretability and integration with decision processes than to identification and assessment (Baryannis *et al*., 2019): the drill-down view explains each score, and the action log ties each score to what was done. Analytics capability contributes to resilience through risk management practice rather than on its own (Liu & Wei, 2022), which is the role the playbook gives the score.

3.4. Matching Warning Time to Mitigation Time

The usefulness of an indicator depends on whether its lead exceeds the time needed to respond. In power-systems manufacturing, responses vary widely in lead time: a bridge buy from distribution stock can take days, re-sequencing production one to two weeks, and qualifying an alternate source of a critical component months. Comparing Table 3 with Table 2 makes the matching concrete. OTD decline, with a two-week lead reduced by one week of confirmation, supports Watch-tier verification and a bridge buy but leaves little or no margin for re-sequencing a constrained build. Lead-time drift and acknowledgment delay, at four to five weeks, cover re-sequencing and pull-forward buys. Even the longest-lead indicator, financial health at eight weeks, falls well short of the months needed to qualify an alternate source of a critical component. For such parts, warning cannot substitute for preparation: dual sourcing or strategic inventory must be decided before any alert, consistent with the distinction between mitigation and contingency strategies (Tomlin, 2006), and the system's role is to signal when to draw on that preparation. The Department of Energy's review of large power transformer supply identified limited domestic grain-oriented electrical steel production and long qualification cycles as structural vulnerabilities (U.S. Department of Energy, 2022b), which places many transformer components, together with large castings, in this category. Managers should therefore map each part family's fastest viable mitigation to the indicators whose lead exceeds it and give longer-lead signals such as supplier financial health and commodity indices more attention for strategic items, even though they are noisier. Upstream capital-project research reaches the same conclusion from the investment side, arguing that long-lead equipment, contractor capacity and logistics feasibility must enter the decision before commitment rather than after it (Nwangwu *et al*., 2021).

3.5. Exposure-Aware Prioritization

The exposure multiplier keeps attention on the parts that matter most. In practice, a manufacturer may track thousands of active supplier-part pairs; without exposure scaling, a commodity spike can trigger alerts across low-risk, multi-source parts and bury the single-source component that actually threatens a utility delivery. Equation (6) makes the effect concrete. A critical ($c = 1$), single-source ($s = 1$) part whose replacement lead time exceeds its coverage ($v = 1$) has $E = 1.0$, whereas a non-critical part with readily qualified alternates and coverage far exceeding its replacement lead time has E close to 0.5. At the same likelihood index of 70, the first scores $R = 70$ and enters the Alert tier, while the second scores about 35 and raises no alert. The multiplier thus implements the observation that disruption severity depends on node criticality (Craighead *et al*., 2007) and that impact should be assessed separately from probability (Simchi-Levi *et al*., 2014). Because Table 4 fixes E at 1.0, its results describe likelihood screening only. Linking exposure to bill-of-materials criticality and customer penalty terms aligns the early-warning system with the firm's continuity-of-supply commitments.

3.6. Governance

Sustained use requires governance. A recommended cadence is weekly review of Alert and Action tiers within the sales and operations planning process, monthly review of supplier drill-downs with category managers, and quarterly recalibration of thresholds and weights from the action log. Supplier collaboration can also improve signal quality: suppliers who share capacity and sub-tier information through portals reduce reliance on indirect proxies. Collaborative risk mitigation depends on the quality of the buyer-supplier relationship (Mwesiumo *et al*., 2021), and suppliers share information more readily when mutual interdependence is recognized (Kembro & Selviaridis, 2015). Firms should therefore be transparent with suppliers about the use of risk scores, explaining which signals drive an escalation, to avoid damaging relationships through unexplained escalation.

3.7. Policy Relevance

Federal policy has emphasized supply chain resilience for critical energy equipment since Executive Order 14017 (2021) and the subsequent Department of Energy supply chain strategy (U.S. Department of Energy, 2022a). The Department's review of large power transformers and high-voltage direct current systems (U.S. Department of Energy, 2022b) assesses vulnerability at the level of the national supply base, whereas the framework here operates at the

supplier-part level inside one manufacturer. Firm-level early-warning capability therefore complements these sector-level efforts: it identifies which suppliers and parts are under stress, while sector-level reviews identify which materials and capacities are scarce. Aggregated, anonymized risk signals from manufacturers could also inform industry and government monitoring of grid equipment supply, much as composite indices such as the Global Supply Chain Pressure Index summarize systemic pressure (Benigno *et al*., 2022), provided that confidentiality constraints on supplier-specific information are respected.

3.8. Limitations and Future Research

Several limitations should be noted. First, the evaluation uses synthetic data. Although the simulation reflects practitioner-reported conditions, actual lead times, noise levels and event frequencies will differ by firm and commodity, the reported values are not out-of-sample estimates, and empirical validation on real shortage logs is the most important next step. Second, disruption events are rare for any single supplier-part pair, which makes threshold and weight estimates unstable early in deployment; pooling by commodity family and Bayesian shrinkage are promising remedies. Third, the framework detects supplier-level stress but has limited visibility into sub-tier suppliers, where many disruptions originate and from which they propagate (Scheibe & Blackhurst, 2018); integrating sub-tier mapping and supplier-shared data is a natural extension. Fourth, the logistic transform and inverse-NTS weights are deliberately simple. Future work could compare them with supervised learning models while preserving interpretability (Baryannis *et al*., 2019), for example through monotonic constraints or feature attribution. Finally, the cost side is not modeled explicitly. A natural extension would choose thresholds by minimizing the expected sum of false-alarm investigation cost and missed-disruption cost.

4. Conclusion

This paper set out a business-intelligence framework for supply-disruption early warning in power-systems manufacturing that links supplier signals to exposure, useful warning time and owned mitigation actions. Indicators enter the score only after qualification by lead time and noise-to-signal ratio, likelihood is separated from exposure, alert thresholds are set by acceptable review workload, and each tier carries pre-approved actions and named owners. The composite score remains a risk propensity index until probability calibration is demonstrated.

The synthetic illustration shows the trade-offs that the framework is designed to manage. On that panel, the composite at its lowest tier detected the same share of disruptions as delivery monitoring with three times the median warning, and raising the threshold improved precision while reducing recall and review workload. Lead-time drift alone performed as well as the composite's middle tier, which suggests that firms can begin with signals already held in their ERP and supplier portal data. These results describe design behavior; they do not establish effectiveness in a manufacturing operation or prove loss prevention.

Implementation depends on a small set of controls that keep escalation auditable: consistent signal definitions with timestamped availability, normalization on historical data only, an unscored status rather than a reassuring zero when indicators cannot be identified, consistent units for coverage and replacement lead time, and measurement of warning time from the first confirmed alert rather than the first threshold crossing. For long-lead strategic parts, where no indicator leads by as much as alternate-source qualification requires, the system complements dual sourcing and strategic inventory rather than replacing them. Reviews of longitudinal data trends in mature asset portfolios show that harmonization and quality control of long, non-stationary records are preconditions for trend analysis (Nwangwu *et al*., 2022), which applies equally to the multi-year supplier histories from which the indicator baselines are computed.

Prospective validation should use temporally separated training and testing with a purge interval covering the prediction horizon, group repeated signals into alarm episodes, and measure missed disruptions, actionable lead time, false alarms, reviewer workload and mitigation completion. Such evidence would allow thresholds to be calibrated for different supplier and product conditions and would show whether linking signals to exposure and response ownership improves continuity of supply in practice.

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