

Supplier Financial Distress and Supply Chain Continuity: An Integrated Early Warning Framework

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Abstract

The financial failure of a supplier is one of the most consequential and least anticipated sources of supply chain disruption. Conventional supplier risk practice relies heavily on periodic credit reports and published financial statements, which arrive late, cover private suppliers poorly, and say nothing about how much a buying firm would actually lose if a given supplier failed. This paper develops an integrated early warning framework that combines four complementary signal families: (1) financial indicators, (2) delivery performance, (3) payment behavior, and (4) concentration risk. The first three pillars are aggregated into a momentum-adjusted *distress likelihood* score, while the fourth pillar measures *continuity impact*, the exposure the buyer faces if the supplier fails. The two dimensions are combined through a geometric Continuity Risk Score and supplemented by hard-trigger overrides for discrete credit events. Scores map to a four-tier alert structure (Green, Amber, Red, Critical) with a corresponding response playbook covering monitoring, sourcing, financial and contractual actions. A stylized application to an eight-supplier portfolio and a simulated failure trajectory illustrates how operational and payment signals can surface distress several months before it becomes visible in financial statements, and how impact weighting changes which suppliers receive management attention. The paper discusses theoretical and practical implications, acknowledges limitations, including data availability for small and private suppliers and the risk that early warning itself becomes a self-fulfilling prophecy, and sets out an agenda for future research built around four testable propositions.

Keywords: supplier financial distress; supply chain continuity; early warning system; supplier risk management; trade credit; concentration risk; business continuity

1. Introduction

Supply chains became markedly more fragile in the years following 2020. The pandemic, logistics bottlenecks, energy price shocks and the rapid tightening of monetary policy in 2022 and 2023 placed sustained pressure on the working capital of small and mid-sized manufacturers, many of which sit in the second and third tiers of larger supply networks. Higher interest rates raised refinancing costs at the same time that input-cost inflation squeezed margins, and corporate insolvency counts in many advanced and emerging economies climbed back above their pre-pandemic levels. For a buying firm, these macroeconomic conditions translate into a very specific operational threat: a supplier that is critical to production may stop shipping, not because of a fire or a flood, but because it has run out of cash.

Supplier insolvency is a distinctive type of disruption. Unlike natural hazards, it usually develops gradually and leaves a trail of observable symptoms: requests for faster payment, falling on-time delivery, quality slippage, staff turnover, and eventually covenant breaches and legal actions. Empirical work shows that the consequences are severe. Hendricks and Singhal (2005) document substantial and persistent negative abnormal stock returns for firms announcing supply chain disruptions, and Wagner, Bode and Koziol (2009) show that supplier defaults are correlated, so that the failure of one supplier is often accompanied by distress among others in the same network. Yang, Birge and Parker (2015) further show that the bankruptcy of a firm reverberates through its supply chain partners. Distress, in other words, is both damaging and, in principle, detectable.

Yet in most organizations the evidence needed to detect it is fragmented. Credit and treasury teams consult external ratings or bureau scores, often annually during onboarding. Procurement and quality teams maintain supplier scorecards focused on cost, delivery and defects. Accounts payable observes which suppliers ask for early payment or change their bank details. Category managers know which suppliers are sole sources and how long it would take to qualify an alternative. Each function holds a partial view, and none of them owns the combined picture. Financial statements, the traditional backbone of distress prediction, compound the problem because private suppliers publish infrequently and with long delays, which means the formal evidence of distress often arrives after the operational damage has begun. Recent work on data-driven procurement risk management and real-time supply chain risk dashboards points in the same direction, calling for procurement, financial and operational data to be brought together into a single risk view (Bello et al., 2023; Filani et al., 2022; Rukh et al., 2024).

This paper responds to that problem by developing an integrated early warning framework for supplier financial distress that is oriented explicitly toward supply chain continuity. The study is guided by three questions: which observable financial, operational and transactional signals provide early warning of supplier distress, and with what lead times; how the likelihood of distress can be combined with the impact of supplier failure into a single prioritization metric that reflects continuity risk rather than credit risk alone; and how such scores should be translated into proportionate, timely and ethically sound management responses.

In addressing these questions, the paper brings together four signal families that are usually monitored separately (financial indicators, delivery performance, payment behavior and concentration risk) in a single scoring model. The model separates the likelihood of distress from the impact of failure, adjusts for the speed of deterioration, escalates immediately on discrete credit events, and links every score to a tiered response playbook. A stylized application shows how the model behaves and yields propositions for empirical testing. The remainder of the paper is organized as follows. Section 2 describes the methodology, Section 3 synthesizes the relevant literature, Section 4 presents the conceptual model, and Section 5 illustrates its application. Section 6 discusses the results, Section 7 sets out theoretical and practical implications, Section 8 acknowledges limitations, Section 9 outlines an agenda for future research, and Section 10 concludes.

2. Methodology

The study follows a conceptual, model-building approach, which is appropriate when a phenomenon is well documented in separate literatures but has not been integrated into a single explanatory or decision model. The research proceeded in three steps.

First, an integrative review of five literature streams (financial distress prediction, supply chain risk and resilience, supplier default and contagion, trade credit and payment behavior, and dependence and concentration) was used to identify candidate indicators and the mechanisms linking them to supplier failure or to its consequences. An indicator was retained when the literature supported a plausible signalling or causal link to distress or to the impact of failure, when the underlying data are routinely available to buying firms, and when the indicator can be refreshed at least quarterly or on an event basis.

Second, the retained indicators were organized into four pillars and formalized into a scoring model. The aggregation logic draws on established practice in credit scoring, statistical process control and early warning systems, and the parameters were set at transparent initial values intended for later calibration. Third, the behavior of the model was examined through a stylized application to a hypothetical eight-supplier portfolio and a simulated failure trajectory. The application is not an empirical validation. Its purpose is to show how the scoring logic operates, to make the trade-offs in the design visible, and to derive propositions that can be tested with real buyer-side data.

3. Literature Synthesis

3.1 Corporate financial distress prediction

The prediction of corporate failure has a long history in accounting and finance. Beaver (1966) showed that individual financial ratios, particularly cash flow to total debt, differ systematically between failing and non-failing firms several years before failure. Altman (1968) combined five ratios through multiple discriminant analysis into the Z-score, which remains the most widely used distress metric in practice. Ohlson (1980) introduced a logistic regression approach (the O-score), and Shumway (2001) argued that discrete-time hazard models, which use the full history of each firm, forecast bankruptcy more accurately than static single-period models. In parallel, structural models descending from Merton (1974) infer default probability from market equity values and volatility, producing measures such as distance to default.

Later work refined both the inputs and the estimation. The ZETA model extended the Z-score with additional variables (Altman et al., 1977), and Zmijewski showed how non-random sampling of failed firms biases distress models (Zmijewski, 1984). Market-based and hazard approaches incorporate equity prices, volatility and industry effects (Bharath & Shumway, 2008; Campbell et al., 2008; Chava & Jarrow, 2004; Duffie et al., 2007; Hillegeist et al., 2004), and models combining accounting, market and macroeconomic variables improve accuracy for listed firms (Hernandez Tinoco & Wilson, 2013). Evidence that financial statements have become somewhat less informative for bankruptcy prediction over time (Beaver et al., 2005) has encouraged statistical learning, variable selection and failure-process methods (Barboza et al., 2017; du Jardin, 2015; Jones et al., 2017; Ravi Kumar & Ravi, 2007; Tian et al., 2015). Most relevant for supplier monitoring, credit models built specifically for small and medium-sized enterprises show that non-financial information such as late filing, payment history and

legal actions adds substantial predictive power to financial ratios (Altman & Sabato, 2007; Altman et al., 2010).

Two features of this literature matter for supplier risk. First, the revised Z"-score, developed for non-manufacturing firms and adapted for emerging market credits (Altman, 2005), removes the market-value and sales-turnover terms and is therefore applicable to private companies. A broad international re-examination by Altman, Iwanicz-Drozdzowska, Laitinen and Suvas (2017) confirms that Z-score variants retain reasonable classification accuracy across many countries, although performance improves when models are re-estimated for local conditions. Second, all accounting-based models share a timeliness constraint: they can only be updated when statements are published. For private suppliers that report annually, a ratio computed today may describe conditions twelve to eighteen months old. Market-based models avoid this problem but apply only to listed firms, which are a small minority of most supplier bases.

Alongside these classical models, a growing body of applied work develops predictive financial analytics for forecasting, budgeting and risk detection (Adelanwa et al., 2023; Agu et al., 2023; Medon & Oduleye, 2024), including budgeting models that combine operational and market signals (Adesuyi et al., 2022) and scenario-based financial modelling for long-term planning (Filani et al., 2023). Financial planning models for sustainable profitability and AI-driven risk assessment frameworks (Eboh & Aliliele, 2024; Medon & Oduleye, 2023) extend this analytical toolkit. Data-driven risk evaluation and financial resilience models designed for emerging market institutions (Akomolafe & Agu, 2019a, 2019b), together with quantitative models of compliance risk in emerging economies (Akomolafe et al., 2023b), are especially relevant where supplier disclosure is thin and formal ratings are unavailable. These contributions are largely conceptual and institution-focused, but they share the premise of this paper: that combining several imperfect data streams yields a more timely view of financial risk than any single ratio.

3.2 Supply chain risk, disruption and supplier default

The supply chain risk management (SCRM) literature has developed largely in parallel. Chopra and Sodhi (2004) classify supply chain risks and argue for tailored mitigation strategies, while Tang (2006a) reviews quantitative models for managing supply and demand risks. Craighead, Blackhurst, Rungtusanatham and Handfield (2007) show that disruption severity depends on network design characteristics such as density, complexity and node criticality. Sheffi and Rice (2005) emphasize redundancy and flexibility as foundations of resilience. Simchi-Levi,

Schmidt and Wei (2014) introduce time-to-recover (TTR) as a practical metric of the exposure created by each node in a supply network, an idea that underpins the impact dimension of the framework proposed here. More recently, Ivanov and Dolgui (2020) frame the question in terms of supply chain viability under prolonged, multi-node stress. This literature is strong on impact and mitigation but typically treats the probability of a supplier failing as an exogenous input rather than something to be continuously estimated.

The conceptual foundations of the field were laid in the early 2000s. Supply risk was defined in terms of the probability and consequence of inbound supply failure (Zsidisin, 2003), an agenda for supply chain risk management was proposed (Jüttner et al., 2003), and resilience was framed as a design property of supply networks (Christopher & Peck, 2004; Kleindorfer & Saad, 2005). Agency theory explains why buyers must monitor suppliers whose incentives and information differ from their own (Zsidisin & Ellram, 2003). Empirical studies link supply chain vulnerability and risk to performance (Wagner & Bode, 2006, 2008; Zhao et al., 2013), and event studies show that supply chain glitches and disruptions destroy shareholder value, with operational slack moderating the damage (Hendricks & Singhal, 2003; Hendricks et al., 2009). Resilience research has since developed conceptual frameworks, capability measures and contingency perspectives (Blackhurst et al., 2011; Brandon-Jones et al., 2014; Chowdhury & Quaddus, 2017; Hohenstein et al., 2015; Kamalahmadi & Parast, 2016; Pettit et al., 2010; Ponomarev & Holcomb, 2009), while reviews map the growth of supply chain risk management as a discipline (Fan & Stevenson, 2018; Ho et al., 2015; Pournader et al., 2020; Sodhi et al., 2012). Research on mitigation shows the value of robust sourcing strategies and of organizational responses to disruption (Bode et al., 2011; Tang, 2006b), and the bullwhip literature explains how information distortion amplifies the operational symptoms of upstream problems (Lee et al., 1997).

Work set in emerging economy contexts reaches similar conclusions. Studies propose risk management and resilience frameworks for critical infrastructure and energy supply chains (Agbabiaka et al., 2019; Ogunwole et al., 2021), composite resilience indices for post-pandemic supply chains (Efobi et al., 2023), and resilience strategies for pharmaceutical supply (Akinleye, 2024; Awulu et al., 2022). Post-pandemic reviews similarly stress visibility and digital tools as foundations of operational continuity (Anene, 2021; Okonkwo et al., 2024e). These contributions strengthen the case for continuity-oriented monitoring, although they

generally address disruption in aggregate rather than the specific pathway of supplier financial failure.

A related stream treats digital visibility and integration as preconditions for continuity. Conceptual models link digital supply chain governance, secure supply chain systems, ERP adoption and agile digital transformation with embedded IT risk controls to logistics performance and operational reliability (Mbonu et al., 2020; Okonkwo et al., 2024a, 2024b, 2024d). End-to-end visibility frameworks, supply chain analytics and predictive logistics models improve traceability, forecasting and bottleneck detection (Akin-Oluyomi & Akhigbe, 2023b; Anene & Clement, 2022; Nnabueze et al., 2021), and governance models stress shared responsibility, compliance and operational quality across tiers and jurisdictions (Akin-Oluyomi & Akhigbe, 2022; Eze et al., 2023; Ominyi et al., 2021). Work on predictive procurement planning, asset lifecycle management and inventory availability shows how materials readiness underpins plant uptime in capital-intensive settings (Okonkwo et al., 2018b, 2023, 2024c), which is precisely the operational outcome that a supplier failure threatens. Platforms for supply chain automation and GIS-enabled ERP procurement (Ahiaeke Patrick et al., 2020; Okonkwo et al., 2024f) reinforce this point. More recent research uses simulation, digital twins, Bayesian networks and artificial intelligence to model ripple effects and anticipate disruptions (Baryannis et al., 2019; Dolgui et al., 2018; Hosseini & Ivanov, 2020; Ivanov, 2018, 2020; Ivanov & Dolgui, 2021), while big data analytics (Wang et al., 2016) and the prediction of supplier disruptions from buyer-side data (Brintrup et al., 2020) demonstrate the feasibility of the data-driven approach proposed here. Studies of large manufacturers show how exposure can be quantified across thousands of suppliers (Simchi-Levi et al., 2015), and the pandemic prompted calls for richer theoretical toolkits for disruption research (Craighead et al., 2020).

A smaller body of operations research models supplier default explicitly. Babich, Burnetas and Ritchken (2007) analyze how correlated default risk among competing suppliers affects a buyer's diversification decisions, showing that diversification is less valuable when defaults are correlated. Babich (2010) examines when a buyer should provide financial subsidies to a risky supplier and how this interacts with capacity ordering. Wagner et al. (2009) provide empirical evidence from the automotive industry that supplier default probabilities are positively dependent, which implies that portfolio-level monitoring is needed rather than supplier-by-supplier assessment. Research in finance and economics reinforces this picture. Financial distress spreads along supply chains to customers and suppliers (Hertzel et al., 2008; Kolay et

al., 2016), credit shocks propagate through supplier-customer links in the credit default swap market (Agca et al., 2022), and shocks to suppliers of specific inputs reduce customer output (Barrot & Sauvagnat, 2016; Carvalho et al., 2021). At the macro level, production networks transmit firm-level shocks into aggregate fluctuations (Acemoglu et al., 2012), and supply networks can be inherently fragile when relationship-specific investments are high (Elliott et al., 2022). Contract design also matters: long-term contracts can be structured to manage the threat of supplier default (Swinney & Netessine, 2009). Yang et al. (2015) show that supplier bankruptcy has spillover effects on customers and that the relationship between the parties shapes how distress is resolved. Together, these studies establish that distress is partly systemic and that buyers have meaningful levers, including financial support, to influence outcomes. Applied research on vendor risk assessment has also begun to use predictive and data-driven models to score suppliers on combined cost, performance and risk criteria (Ahiaeke Patrick et al., 2021; Tonoyan et al., 2024a), and structured supplier risk assessment frameworks have been proposed for regulated international procurement (Akin-Oluyomi et al., 2023b). Continuous supplier risk intelligence, which replaces annual questionnaires with ongoing supplier profiling and Bayesian risk scoring, has been developed for supplier cyber risk (Smart, 2023), and the same monitoring architecture can carry financial distress signals. These models typically weight financial health as one criterion among many, however, rather than tracking distress dynamically.

Procurement research increasingly embeds risk into sourcing decisions, from strategic procurement optimization and regulatory-compliant sourcing in high-risk energy environments (Okonkwo et al., 2018a, 2021) and negotiation optimization for procurement cost reduction (Akinleye & Adeyoyin, 2022a) to process automation, big data, business intelligence and integrated digital platforms that raise transparency in procurement (Akinleye & Adeyoyin, 2021; Akinleye et al., 2023; Okoruwa et al., 2024). Comparative work on procurement cost optimization across the United Kingdom, Nigeria and other emerging economies (Akokodaripon et al., 2023) shows that the cost pressure buyers place on suppliers differs markedly by context, which matters because aggressive cost reduction can itself weaken supplier finances.

3.3 Trade credit, payment behavior and dependence

Trade credit is a major source of short-term financing, and changes in how firms use it are informative. Petersen and Rajan (1997) show that firms turn to trade credit when institutional

credit is unavailable, which means that a supplier's sudden interest in faster payment from its customers, or its slower payment to its own vendors, often reflects tightening bank credit. Suppliers also act as liquidity providers and debt collectors for their customers (Cuñat, 2007), and trade credit links transmit corporate failure from customers to suppliers (Jacobson & von Schedvin, 2015), so payment behavior is both a symptom and a channel of distress. Research on financial supply chain management (Wuttke, Blome & Henke, 2013) and supply chain finance (Gelsomino, Mangiaracina, Perego & Tumino, 2016) documents the growing use of reverse factoring, dynamic discounting and related instruments. A useful by-product of these programs is a rich stream of behavioral data: which suppliers accelerate invoices, how often, at what discount, and how that pattern changes over time. Buyers therefore hold privileged, high-frequency information about their suppliers' liquidity that is not available to external credit agencies. The digitization of supplier payments, including smart contract automation and digital dispute resolution, further increases the granularity of this data (Akomolafe et al., 2022, 2024), and AI-based risk scoring of trade payment transactions shows how such records can be turned into real-time risk signals (Adesuyi et al., 2024). On the supplier side, predictive models of cash flow and working capital (Oduleye & Medon, 2023a; Tonoyan et al., 2021) clarify the liquidity mechanisms whose strain payment behavior reveals.

The wider payment ecosystem shapes how quickly liquidity strain becomes visible. Fintech-enabled transaction banking, digital lending and high-throughput collections platforms have broadened SME access to working capital in emerging markets (Okafor et al., 2021; Osuji et al., 2021), while trade finance and distributorship products influence how suppliers fund the gap between production and payment (Agboada et al., 2018). Monitoring controls designed for cross-border payment operations (Okafor et al., 2024) and tiered treasury architectures for cash flow consolidation and foreign exchange risk control (Dada et al., 2021) provide design patterns that can be adapted to the payment pillar of a supplier early warning system.

Kraljic (1983) established the principle that purchasing strategy should reflect both profit impact and supply risk, an idea that has shaped category management for four decades. Concentration can be measured with the Herfindahl-Hirschman Index (Hirschman, 1964) at the category level, while network approaches such as that of Kim, Choi, Yan and Dooley (2011) assess structural importance across a supply network. Later research refined the Kraljic portfolio through a power and dependence lens and addressed its measurement challenges (Caniëls & Gelderman, 2005; Gelderman & van Weele, 2003), showed that dependence

asymmetry and joint dependence shape performance in procurement relationships (Gulati & Sytch, 2007), and linked the complexity of the supply base to risk and responsiveness (Choi & Krause, 2006). Supplier development and evaluation research (Ho et al., 2010; Krause et al., 2007) shows that buyers can strengthen suppliers as well as choose among them. For continuity purposes, dependence is bidirectional. A buyer is exposed when a large share of a critical input comes from one supplier, but the supplier is also exposed when a large share of its revenue comes from the buyer, since the buyer's own ordering decisions can then push the supplier into or out of distress. Supplier relationship management research adds that mutual dependence also creates room for collaboration and joint resilience building, which matters when deciding whether to support or exit a distressed supplier (Akin-Oluyomi et al., 2024; Akinleye & Adeyoyin, 2022b; Ike et al., 2021).

3.4 Synthesis of the literature

Taken together, these streams provide the building blocks for supplier early warning but leave them largely unconnected. Table 1 summarizes the contribution and limitation of each stream. The central gap is integration: distress prediction models estimate probability without regard to operational impact, SCRM models estimate impact while treating probability as given, and the transactional and operational data held by buyers are rarely used as formal distress predictors. An early warning framework for continuity must combine all three.

Table 1. Literature streams relevant to supplier distress early warning

Stream	Core contribution	Limitation for continuity management
Distress prediction (Beaver; Altman; Ohlson; Shumway; Merton)	Validated statistical models of failure probability	Lagging accounting data; limited coverage of private suppliers; ignores impact on the buyer
SCRM and resilience (Chopra & Sodhi; Tang; Craighead et al.; Simchi-Levi et al.)	Impact, network criticality, time-to-recover, mitigation design	Treats supplier failure probability as exogenous or static
Supplier default models (Babich et al.; Wagner et al.; Yang et al.)	Correlated default, financial support, contagion	Mostly analytical or sector-specific; few operational monitoring tools
Trade credit and SCF (Petersen & Rajan; Wuttke et al.; Gelsomino et al.)	Liquidity mechanisms and their behavioral footprint	Payment behavior rarely formalized as a distress signal
Concentration and dependence (Kraljic; Hirschman; Kim et al.)	Portfolio and network exposure measures	Static segmentation, not linked to dynamic distress signals

4. Conceptual Model: An Integrated Early Warning Framework

4.1 Design principles and architecture

The conceptual model is built on design principles derived from the literature synthesized in Section 3. They also draw on the supply chain performance measurement tradition, which argues for balanced, multi-dimensional metric sets linked to strategy (Beamon, 1999; Gunasekaran et al., 2004; Kaplan & Norton, 1992).

Six principles follow from this. The framework relies on multi-source evidence, combining financial, operational, transactional and structural data so that weaknesses in one stream are offset by strengths in another. It favors leading over lagging indicators, selecting and weighting signals for their timeliness as well as their statistical association with failure. It measures the likelihood of distress and the impact of failure separately and combines them explicitly, so that neither dominates by accident. It considers trends as well as levels, because deterioration is often more informative than the absolute value of a metric. It is proportionate, degrading gracefully when indicators are missing and reporting a data confidence level with each score. Finally, it is actionable: every score maps to a defined tier, owner, review cadence and set of permissible responses.

Figure 1 shows the architecture. Layer 1 collects indicators within four pillars. Layer 2 aggregates the financial, delivery and payment pillars into a distress likelihood score and the concentration pillar into a continuity impact score. Layer 3 combines the two into a Continuity Risk Score, applies hard-trigger overrides, and assigns an alert tier.

4.2 Indicator pillars

Financial indicators. The financial pillar captures the supplier's capacity to meet obligations. It combines ratio-based measures of liquidity, leverage and profitability with an overall solvency score and with external and legal events. For private suppliers the Z"-score is preferred to the original Z-score because it does not require a market value of equity. Where the supplier is listed, market-implied measures such as equity-based distance to default or credit default swap spreads add a forward-looking, high-frequency component. External signals include rating or bureau-score downgrades, auditor going-concern qualifications, registered charges or liens, court judgments, and changes in ownership or senior management. Because statements arrive infrequently, the pillar is updated quarterly where possible, with event-driven updates whenever an external signal fires. Where suppliers share management accounts,

variance analytics and data-driven cost management models (Aliliele et al., 2024; Oduleye & Medon, 2021) help distinguish temporary margin pressure from structural erosion, and quantitative evidence on the strategic value of financial analysis (Oduleye & Medon, 2023b) supports investment in this capability.

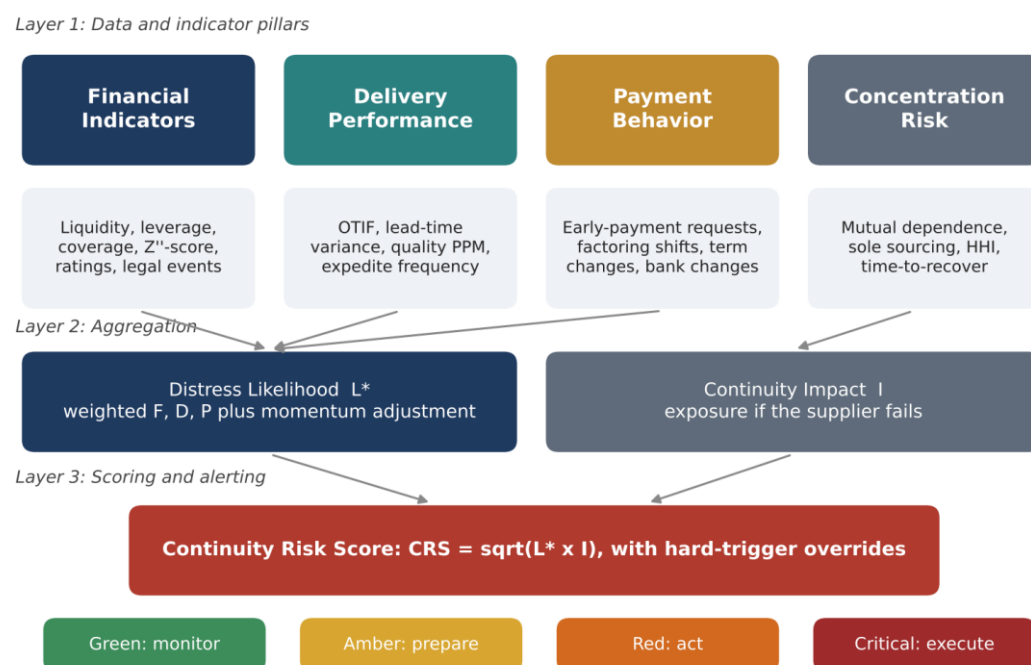


Figure 1. Architecture of the integrated early warning framework

Delivery performance. Delivery performance is the operational expression of distress. A supplier short of cash tends to delay raw material purchases, defer maintenance, lose skilled staff and prioritize customers who pay fastest. These choices surface as falling on-time-in-full (OTIF) rates, more variable lead times, higher defect rates, more frequent partial shipments, and more requests from the buyer's side for expediting. The key analytical step is to distinguish distress-driven deterioration from ordinary noise or from disruption caused by the buyer's own demand volatility. The framework therefore monitors each delivery metric relative to the supplier's own baseline using exponentially weighted moving average (EWMA) or cumulative sum (CUSUM) control charts (Lucas & Saccucci, 1990; Page, 1954; Roberts, 1959), and flags sustained shifts rather than single bad months. Anomaly detection approaches developed for financial time series (Atakpa & Fobellah, 2023) and automated real-time KPI tracking systems (Tonoyan et al., 2024b) provide practical tools for running this monitoring at scale. Statistical time-series forecasting models (Atakpa et al., 2024) can additionally project where each metric is heading, not only where it stands. Workforce signals deserve attention as well: staffing

volatility and rising turnover often precede service deterioration, and operational analytics frameworks that integrate workforce and risk data (Falemi et al., 2023, 2024) show how such signals can be captured. Process capability measures from Lean Six Sigma practice in manufacturing (Ezeugwa et al., 2023) offer a further lens on quality slippage. Lead-time variability often originates in logistics bottlenecks, port demurrage and throughput constraints rather than in the supplier itself (Akinola et al., 2024; Efobi et al., 2022b; Nwangwu et al., 2024; Okonkwo et al., 2020), so the delivery pillar should separate supplier-caused delays from logistics-caused delays before scoring them. Performance is also compared with other suppliers in the same category to separate supplier-specific problems from market-wide constraints.

Payment behavior. Payment behavior is the pillar most specific to the buyer's privileged position. When a supplier's bank lines tighten, it typically tries to accelerate cash collection from customers before it formally reports any problem. The buyer observes this directly through requests for early payment, increased uptake of dynamic discounting or reverse factoring, acceptance of steeper discounts, requests to shorten payment terms, a rise in invoice disputes or duplicate invoicing, and changes to remittance bank accounts or assignment of receivables to a third-party factor. Where data are available from trade credit bureaus, the supplier's own days beyond terms with its vendors provide the mirror image of the same liquidity strain. Bank-detail changes deserve special attention because they are both a distress signal and a common vector for payment fraud, so they should trigger verification as well as scoring, drawing on the adaptive transaction risk scoring used in payment fraud monitoring (Fadayomi et al., 2024). Machine learning methods reviewed for financial fraud detection (Atakpa & Abetoh, 2022) can help separate legitimate account changes from manipulation.

Concentration risk. Concentration risk measures how badly the buyer would be affected if the supplier failed, and it is deliberately kept separate from the likelihood pillars. It includes the buyer's dependence on the supplier (share of category spend and share of critical part numbers), single-source and sole-source status, the estimated time to qualify and ramp up an alternative relative to the time the buyer can survive on inventory (the TTR and time-to-survive logic of Simchi-Levi et al., 2014), the revenue impact of the products the supplier feeds, and the category Herfindahl-Hirschman Index. It also includes the supplier's dependence on the buyer, because a supplier that derives a large share of its revenue from one customer is both more fragile and more open to supportive intervention. Geographic and sub-tier concentration, for example several suppliers relying on the same tier-two foundry or the same port, capture

correlated exposure of the kind documented by Wagner et al. (2009). For cross-border suppliers, export controls, sanctions regimes and customs processes add a further layer of geographic exposure that should be reflected in the concentration pillar (Jones & Ominyi, 2023, 2024).

Table 2 lists the recommended indicators for all four pillars, together with their direction, typical data source and update frequency.

Table 2. Indicator set by pillar

Pillar	Indicator	Risk rises when	Source	Frequency
Financial (F)	Current and quick ratio	Ratio falls	Financial statements	Quarterly or annual
	Net debt / EBITDA; interest coverage	Leverage rises; coverage falls	Financial statements	Quarterly or annual
	EBITDA margin trend	Margin contracts	Financial statements	Quarterly or annual
	Altman Z"-score	Score falls toward distress zone	Derived	Quarterly or annual
	Rating or bureau score; CDS or distance to default (listed)	Downgrade; spread widens	Agencies, bureaus, markets	Daily to monthly
	Liens, judgments, going-concern opinion, ownership change	Any new event	Registries, news monitoring	Event-driven
Delivery (D)	OTIF rate	Sustained decline vs. baseline	ERP receipts	Weekly or monthly
	Lead-time mean and variance	Mean or variance rises	ERP	Monthly
	Quality defects (PPM), returns	Defects rise	Quality system	Monthly
	Partial shipments; expedite requests	Frequency rises	ERP, buyer logs	Monthly
	Unplanned substitutions, capacity warnings	Any occurrence	Supplier communication	Event-driven
Payment (P)	Early-payment and discount requests	Frequency or discount depth rises	AP, SCF platform	Monthly
	Factoring or SCF uptake share	Share of invoices accelerated rises	SCF platform	Monthly
	Payment-term shortening requests	Any request	Procurement	Event-driven
	Bank detail change; receivables assignment	Any change	AP vendor master	Event-driven

Pillar	Indicator	Risk rises when	Source	Frequency
	Supplier's days beyond terms to its vendors	Days rise	Trade credit bureau	Monthly
Concentration (C)	Buyer share of category spend from supplier	Share rises	Spend cube	Quarterly
	Single or sole source status	Sole source	Sourcing records	Quarterly
	Time-to-recover vs. time-to-survive	TTR exceeds TTS	Category and planning teams	Semi-annual
	Revenue at risk from dependent products	Revenue at risk rises	Bill of materials, sales data	Quarterly
	Supplier revenue share from buyer	Share very high or falling sharply	Supplier disclosure, estimates	Annual
	Category HHI; geographic and sub-tier overlap	Concentration rises	Spend and sub-tier mapping	Annual

4.3 Scoring model

Each raw indicator x is first winsorized at the 5th and 95th percentiles of its peer distribution and then transformed to a 0 to 100 risk scale, oriented so that higher values always mean higher risk:

$$\tilde{x}_i = 100 \times (x_i - x_{\min}) / (x_{\max} - x_{\min}) \quad (1)$$

where $x_{\min}$ and $x_{\max}$ are the winsorized bounds of the peer group, reversed for indicators where lower raw values mean higher risk. Where peer data are thin, expert-defined threshold bands (for example, OTIF above 95 percent scores 0 and below 80 percent scores 100) can replace the empirical bounds. Within each pillar k , normalized indicators are combined as a weighted average:

$$S_k = \sum_i w_{ki} \tilde{x}_{ki}, \quad \text{with } \sum_i w_{ki} = 1 \quad (2)$$

When an indicator is missing, its weight is redistributed proportionally across the indicators that are available, and the share of total weight actually observed is reported as the supplier's data confidence level. The three likelihood pillars are then combined into a baseline distress likelihood:

$$L = \alpha_F F + \alpha_D D + \alpha_P P, \quad \text{with } \alpha_F = 0.45, \alpha_D = 0.30, \alpha_P = 0.25 \quad (3)$$

The initial weights reflect expert judgment: financial indicators remain the best validated predictors of eventual failure, but delivery and payment signals carry substantial weight

because of their timeliness. In practice the weights should be recalibrated once historical outcome data are available (Section 4.4). Because deterioration is often more informative than level, a momentum adjustment is applied:

$$L^* = \min(100, L + \beta \times \max(0, \Delta L_{3m})) \quad (4)$$

where ΔL_{3m} is the change in L over the previous three months and β (set at 0.5 initially) controls how strongly rapid deterioration is penalized. Improvements are not rewarded symmetrically, which builds in a deliberate conservatism: a supplier must demonstrate sustained recovery rather than a single good month. Continuity impact I is computed from the concentration indicators in the same way as Equation (2). Finally, likelihood and impact are combined in a geometric Continuity Risk Score:

$$CRS = \sqrt{L^* \times I} \quad (5)$$

The geometric form has three useful properties. It stays on the 0 to 100 scale, it ensures that a supplier scores highly only when both likelihood and impact are material, and it preserves the interaction between the two: a distressed but easily replaced supplier and a healthy but irreplaceable one both receive moderate scores, while a distressed and irreplaceable supplier rises sharply. The full two-dimensional position (L, I^*) is also retained, because, as Section 4.5 shows, the appropriate response depends on which dimension drives the score.

Some events are so strongly associated with imminent failure that they should not be diluted by averaging. The framework therefore defines hard triggers that escalate a supplier immediately, regardless of its computed score, whenever continuity impact is material ($I \geq 50$). Typical hard triggers include a formal insolvency, administration, receivership or creditor-protection filing or a winding-up petition; a covenant breach, covenant waiver or withdrawal of a major credit facility; missed payroll, tax or statutory payments, or reports of unpaid sub-tier vendors halting supply; an auditor's going-concern qualification or resignation; and the loss of a major customer or a sudden ownership change to an unknown or highly leveraged acquirer.

For suppliers with low impact, the same events raise the tier by one level rather than forcing a Critical rating, preserving proportionality.

Finally, the Continuity Risk Score maps to four alert tiers, each with a defined meaning and review cadence (Table 3). The logic mirrors early warning systems in other supply domains, such as models for essential medicine shortages that tie monitored signals to predefined

response levels (Eze et al., 2022). The thresholds shown are starting points and should be tuned to the organization's risk appetite and the cost of acting on false alarms.

Table 3. Alert tiers, thresholds and review cadence

Tier	CRS range	Interpretation	Review cadence
Green	Below 35	No material continuity concern	Quarterly automated refresh
Amber	35 to below 55	Emerging concern or high structural exposure; prepare contingencies	Monthly review by category owner
Red	55 to below 75	Probable distress with material impact; active mitigation required	Fortnightly review by risk council
Critical	75 and above, or hard trigger with $I \geq 50$	Failure plausible within the planning horizon; execute continuity plan	Weekly or daily executive oversight

4.4 Calibration and validation

The framework is designed to start with expert weights and improve with evidence. Once an organization has accumulated a history of supplier outcomes, including insolvencies, forced restructurings, supply interruptions and emergency financial support, the pillar weights can be re-estimated using a discrete-time hazard model in the spirit of Shumway (2001), with the pillar scores and their momentum as time-varying covariates. Where outcome events are too rare for statistical estimation, structured expert elicitation such as the Analytic Hierarchy Process (Saaty, 1980) offers a transparent alternative. Validation should report at least three measures: discrimination (the area under the receiver operating characteristic curve), median lead time between first Amber or Red alert and the distress event, and the false alarm rate per hundred suppliers monitored. These measures follow standard practice in classifier evaluation (Fawcett, 2006; Hanley & McNeil, 1982) and in the signals approach to early warning, where each indicator is judged by the trade-off between missed crises and false alarms (Kaminsky et al., 1998). Thresholds should then be set by weighing the cost of an unnecessary contingency action against the much larger expected cost of an undetected failure in a high-impact supplier.

4.5 Response playbook and governance

An early warning system creates value only if it changes decisions. Table 4 sets out the default responses by tier across four action families: monitoring, sourcing, financial and contractual.

Table 4. Response playbook by alert tier

Tier	Monitoring	Sourcing and operations	Financial	Contractual and legal
Green	Automated refresh; annual supplier review	Standard sourcing strategy	Standard payment terms; SCF available on request	Standard terms
Amber	Monthly review; request interim accounts; open dialogue with supplier	Map sub-tier dependencies; identify and pre-qualify alternates; review safety stock	Monitor SCF usage; consider offering early payment at fair discount	Confirm tooling ownership, IP and step-in rights
Red	Fortnightly review; site visit; management meeting	Qualify second source; build strategic buffer; prepare demand transfer plan	Targeted support: prepayment for materials, reverse factoring, short-term credit if strategic	Document escrow, consignment stock, reinforce assignment and title clauses
Critical	Weekly or daily monitoring; on-site presence where justified	Execute transfer; last-time buys; recover tooling	Decide between structured rescue support and controlled exit	Engage legal counsel; protect assets and inventory in insolvency proceedings

The appropriate response also depends on which dimension drives the score. Figure 2 in Section 5 divides the likelihood-impact plane into four quadrants. Suppliers with low likelihood but high impact warrant *strategic watch*: they are not in trouble, but their failure would be severe, so redundancy should be built while there is time. Suppliers with high likelihood but low impact call for *managed exposure*: limit new business and replace on a normal sourcing cycle. Suppliers with both high likelihood and high impact require *intervention*, where the central decision is whether to support the supplier through recovery or to exit in a controlled way. Babich (2010) shows that financial support can be value-creating for a buyer when switching is costly, which is precisely the situation in this quadrant.

Contractual preparation is far easier before distress becomes visible. Reviews of force majeure and contractual resilience in global supply chains (Uchechi et al., 2020) and of vendor governance in contract negotiation (Okonkwo et al., 2019) underline the value of agreeing step-in rights, tooling ownership, information-sharing obligations and transition assistance at the start of the relationship, so that the Red and Critical responses in Table 4 can be exercised without dispute.

Standardized contract review workflows and liability mitigation practices for high-value service contracts (Uchechi & Ominyi, 2019; Uchechi et al., 2021) help apply these provisions consistently across the supplier base rather than negotiating them case by case.

Because the four pillars draw on data owned by different functions, the framework requires a cross-functional governance structure. A supplier risk council chaired by the chief procurement officer or chief supply chain officer, with standing members from treasury or credit, accounts payable, quality, supply planning and legal, should own the thresholds, review Red and Critical suppliers, and approve financial support or exit decisions. Each pillar needs a named data owner responsible for data quality and refresh frequency. Decisions taken in response to alerts should be logged, both for accountability and to build the outcome history required for calibration. Tier status should be presented through performance dashboards and standardized reporting workflows that give leaders consistent visibility (Alieme et al., 2022; Babatope et al., 2023; Ezeako et al., 2024), including procurement profitability analysis tools (Akin-Oluyomi et al., 2020), supported by KPI frameworks that assign clear accountability for each metric (Akin-Oluyomi & Akhigbe, 2023a; Sakyi et al., 2022). Periodic internal review of the framework itself, following risk-based auditing principles (Akomolafe et al., 2023a) together with technology-enabled internal audit risk assessment and audit analytics (Abetoh & Atakpa, 2024; Akomolafe & Agu, 2018), provides assurance that thresholds and data feeds remain fit for purpose.

Two ethical and strategic safeguards deserve emphasis. First, supplier data must be handled confidentially and in line with contractual and data protection obligations, particularly where suppliers share interim accounts in good faith. Privacy-preserving data architectures developed for regulated industries (Atakpa & Abolaji, 2022) offer a model for storing and sharing such information securely. Second, the system can become a self-fulfilling prophecy: if every Amber alert triggers a reduction in orders, the buyer may itself push a recoverable supplier into failure. The playbook therefore privileges preparation and dialogue at Amber, reserves volume withdrawal for confirmed and high-likelihood cases, and requires an explicit support-versus-exit assessment before reducing business with a strategically important supplier.

Organizations can implement the framework in three phases. In the **foundation** phase (roughly the first three months), the focus is on segmenting the supplier base, computing the concentration pillar for the top suppliers by spend and criticality, and connecting the existing ERP, accounts payable and supplier finance data. In the **integration** phase (months four to nine), all four pillars are scored for critical suppliers, control charts are established for delivery metrics, hard triggers are automated through registry and news monitoring, and the risk council begins monthly reviews. In the **optimization** phase (from month ten), weights and thresholds

are recalibrated against observed outcomes, coverage is extended to tier-two suppliers for the most critical categories, and the scores are integrated into sourcing, sales and operations planning, and business continuity processes.

Organizations with limited analytics maturity, including many mid-sized firms in emerging markets, can benefit from structured readiness assessment and phased adoption approaches of the kind proposed for AI adoption in SMEs (Alieme et al., 2023), which reduce the risk of building sophisticated scores on unreliable data.

5. Illustrative Application

This section applies the framework to a stylized portfolio. The data are hypothetical and were constructed to demonstrate the mechanics of the model and the type of insight it produces. They are not empirical estimates, and the patterns shown should be read as illustrations of the propositions in Section 9 rather than as evidence for them.

5.1 Portfolio scoring

Consider a mid-sized manufacturer with eight monitored suppliers across packaging, materials, components and logistics. Table 5 reports the pillar scores, baseline and momentum-adjusted likelihood, impact, Continuity Risk Score and resulting tier, computed using Equations (3) to (5) with $\beta = 0.5$. Figure 2 plots each supplier on the likelihood-impact plane.

Table 5. Illustrative scores for an eight-supplier portfolio (hypothetical data)

Supplier	Category	F	D	P	L	ΔL_{3m}	L^*	I	CRS	Tier
S-01	Packaging film	20	15	18	18.0	0	18.0	22	19.9	Green
S-02	Specialty resin (sole source)	30	24	26	27.2	0	27.2	71	43.9	Amber
S-03	Corrugated cartons	44	38	36	40.2	+2	41.2	34	37.4	Amber
S-04	Machined components (hard trigger: covenant waiver)	62	64	70	64.6	+9	69.1	78	73.4	Critical
S-05	Logistics (3PL)	55	62	58	57.8	+3	59.3	30	42.2	Amber
S-06	Electronic sub-assemblies	30	40	38	35.0	+4	37.0	58	46.3	Amber
S-07	Labels and printing	22	20	24	21.9	0	21.9	45	31.4	Green
S-08	Precision castings	42	46	52	45.7	+10	50.7	83	64.9	Red

Note: F , D , P and I are pillar scores on a 0 to 100 risk scale. $L = 0.45F + 0.30D + 0.25P$; $L = L + 0.5 \times \max(0, \Delta L_{\{3m\}})$; $CRS = \sqrt{L \times I}$.

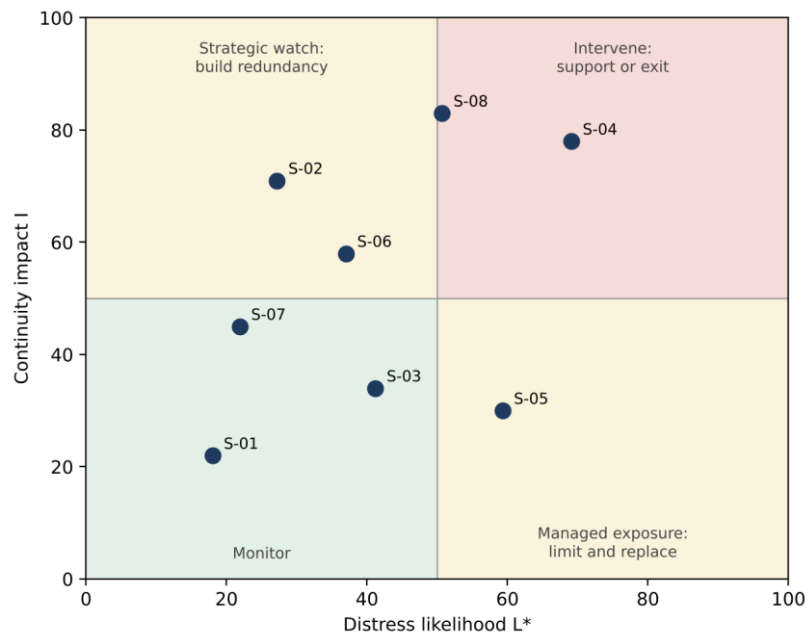


Figure 2. Supplier positions on the likelihood-impact plane (hypothetical data)

Four observations stand out. First, **S-04** (machined components) is rated Critical. Its composite score of 73.4 would on its own place it in the upper part of the Red tier, but a recent covenant waiver acts as a hard trigger and, because its impact score of 78 exceeds 50, the supplier is escalated directly to Critical. Second, **S-08** (precision castings) illustrates why integration matters. Its financial score of 42 is unremarkable and would not attract attention in a credit-only screen. However, its payment score of 52 and a three-month deterioration of 10 points lift its adjusted likelihood to 50.7, and its very high impact (83) produces a CRS of 64.9, a Red alert. This is the profile of a supplier whose distress is visible in transactional data well before it reaches the financial statements.

Third, **S-05** (a logistics provider) has the second-highest baseline likelihood in the portfolio (57.8), yet it receives only an Amber rating because the impact of its failure is limited ($I = 30$): alternative carriers can be engaged quickly. A likelihood-only system would place S-05 near the top of the watch list and consume scarce management attention on a supplier whose failure would be an inconvenience rather than a continuity threat. Fourth, **S-02** (a sole-source specialty resin supplier) is financially healthy ($L = 27.2$) but scores Amber because of its high impact ($I = 71$). The recommended response is not financial intervention but strategic redundancy: qualification of an alternate resin and review of safety stock while the supplier is stable and cooperative.

5.2 Signal lead times in a failure trajectory

Figure 3 shows a simulated monthly trajectory for a supplier in the eighteen months before an insolvency filing. The simulation encodes the sequence suggested by the literature on trade credit and operational distress: liquidity strain shows up first in payment behavior, then in delivery performance as the supplier starts rationing materials and labor, and only later in published financial statements, which are updated quarterly with a reporting lag.

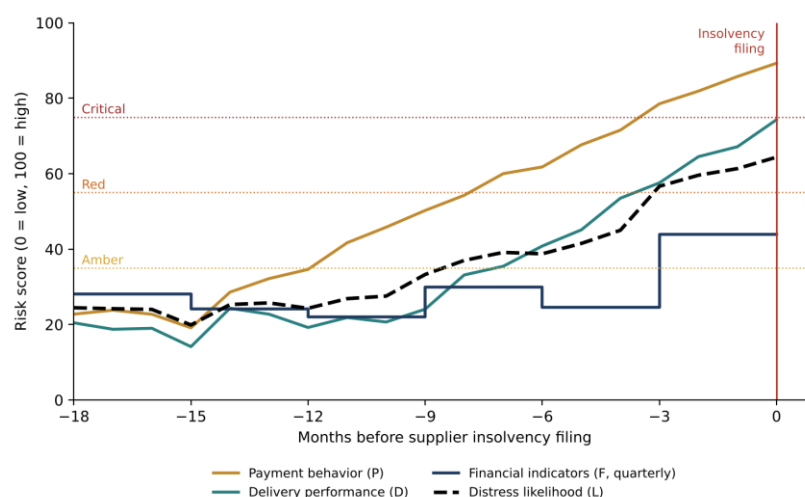


Figure 3. Simulated pillar and composite scores before a supplier insolvency (illustrative)

In this illustration the payment pillar crosses the Amber threshold about twelve months before the filing and the Red threshold about eight months before. Delivery performance crosses Amber about seven months before the filing. The composite likelihood crosses Amber roughly nine months out and Red roughly three months out. The financial pillar, by contrast, does not reach the Amber threshold until the final quarterly update, about three months before the filing. The practical implication is the difference between having nine months and having three months to qualify an alternate source, which for many engineered components is the difference between a managed transition and a line stoppage.

6. Discussion

The conceptual model and its illustrative application point to three observations. First, the timing of signals matters as much as their strength. In the simulated trajectory, payment and delivery signals crossed alert thresholds many months before financial indicators did. This pattern is consistent with the view that suppliers draw on trade credit and customer prepayments when bank credit tightens (Petersen & Rajan, 1997) and that trade credit links

transmit corporate failure between firms (Jacobson & von Schedvin, 2015). It also echoes evidence that non-financial information adds substantial predictive power to credit models for smaller firms (Altman et al., 2010). A buyer that monitors only financial statements is therefore likely to learn of distress late.

Second, prioritization changes once impact is considered. In the illustrative portfolio, the supplier with one of the highest distress likelihoods received only an Amber rating because its failure would be easy to absorb, whereas a supplier with an unremarkable financial profile but very high impact was escalated to Red. This is consistent with the long-standing argument that supply strategy should reflect both supply risk and business impact (Kraljic, 1983) and with exposure metrics such as time-to-recover (Simchi-Levi et al., 2014). Third, the appropriate response depends on why a supplier scores highly. Distressed but critical suppliers raise the question of whether to support or exit, where buyer financial support can be value-creating (Babich, 2010), while healthy but critical suppliers call for redundancy built in advance. Given the documented costs of disruption for buying firms (Hendricks & Singhal, 2005), these distinctions carry real financial weight.

6.1 Data-scarce and emerging market settings

In many emerging markets, a large share of suppliers are small private firms with limited or delayed financial disclosure, credit bureau coverage is incomplete, and currency volatility can rapidly change the solvency of firms with foreign-currency costs or debt. In these settings, the relative weight of the delivery and payment pillars should be increased, the Z"-score variant adapted for emerging markets should be used where statements exist, and additional indicators such as foreign-currency exposure, dependence on imported inputs and access to foreign exchange can be added to the financial pillar. Data-driven risk evaluation models developed for emerging market financial institutions (Akomolafe & Agu, 2019b) offer useful templates for this local adaptation. Regulatory barriers to import-export participation for local firms (Jones & Ominyi, 2020) and the growing ESG expectations placed on SME suppliers in emerging economies (Akinleye, 2023; Okojie et al., 2020) can add to financial strain, and should be considered alongside conventional distress signals. Green and sustainable procurement requirements for local manufacturers in Africa (Akin-Oluyomi et al., 2023a; Efobi et al., 2022a) and localized supply chain strategies for regional resilience (Anene & Clement, 2024) point in the same direction: supporting capable local suppliers can reduce concentration risk, but only if their financial health is monitored. The proportionality principle and the data

confidence measure are particularly important here, so that a supplier with sparse data is not mistaken for a supplier with low risk.

7. Implications

7.1 Theoretical implications

The framework connects two literatures that have largely developed separately. Distress prediction research asks whether a firm will fail; supply chain risk research asks what happens to its partners if it does. By formally combining likelihood and impact, the framework reframes supplier distress as a continuity problem rather than a credit problem. It also highlights an information asymmetry that has received little attention: buyers observe operational and payment signals about their suppliers that are unavailable to banks, rating agencies or investors. In this sense the buyer is not merely a passive victim of supplier failure but a potentially well-informed monitor, and, as Babich (2010) and Yang et al. (2015) suggest, sometimes an active participant in how distress is resolved.

7.2 Practical implications

For practitioners, the most immediate implication is that much of the data required for early warning already exists inside the organization, distributed across ERP, accounts payable, quality and supplier finance systems. The principal investment is in integration and governance rather than in purchased data. Second, supplier finance programs should be viewed not only as working capital tools but also as monitoring instruments, provided that the information is used to support suppliers rather than to penalize them for using a facility the buyer itself offers. Third, impact assessment should be refreshed at least annually, because concentration changes as product portfolios evolve, and a supplier that was easily substitutable two years ago may now be sole-sourced. Finally, the playbook's emphasis on graduated response helps organizations avoid both complacency and overreaction. Experience with digital transformation and predictive strategic insight in large service organizations (Nnabueze et al., 2023; Sakyi et al., 2024) suggests that such frameworks deliver most value when embedded in routine decisions rather than run as stand-alone projects. Treating suppliers as a portfolio, in the spirit of portfolio risk optimization models used in investment settings (Eboh & Aliliele, 2023), also helps managers recognize that correlated exposures can matter more than any single supplier's score.

8. Limitations

Several limitations should be acknowledged. First, the default weights and thresholds are based on expert judgment and the literature rather than on estimation from a specific dataset, and they will need local calibration. Second, the illustrative application uses hypothetical data and cannot demonstrate predictive validity; the propositions in Section 9 require empirical testing. Third, supplier failures are rare events for most individual buyers, which makes statistical calibration difficult without pooling data across business units or industry consortia. Fourth, some signals, notably early-payment requests, can reflect rational treasury optimization rather than distress, which is why the framework relies on changes relative to each supplier's own baseline and on corroboration across pillars. Fifth, the framework focuses on direct suppliers; sub-tier distress is captured only partially through concentration indicators and supplier disclosures. Finally, there are legal and ethical constraints on how supplier information may be collected, shared and acted upon, which vary by jurisdiction and contract.

9. Future Research

The framework and the illustration suggest four propositions for empirical research using buyer-side supplier data linked to distress outcomes. The first concerns signal sequence: deterioration in supplier payment behavior precedes deterioration in delivery performance, which in turn precedes deterioration in published financial indicators (P1). The second concerns the value of integration: a likelihood score combining financial, delivery and payment pillars achieves higher discrimination and a longer median lead time than a financial-only score (P2). The third concerns momentum: momentum-adjusted scores reduce missed detections among rapidly deteriorating suppliers without a proportionate increase in false alarms (P3). The fourth concerns impact weighting: prioritizing suppliers by a combined likelihood-impact score reduces the realized disruption cost per alert investigated compared with prioritization by likelihood alone (P4).

Beyond these propositions, several avenues merit attention. Pooling outcome data across business units or industry consortia would make statistical calibration of the pillar weights feasible despite the rarity of supplier failures. Extending the model to tier-two and tier-three suppliers, for example through sub-tier mapping and shared data platforms, would capture correlated exposures that direct monitoring misses. Comparative studies across sectors and countries, including data-scarce emerging markets, could test whether the relative value of

payment and delivery signals rises where financial disclosure is weak. Finally, field studies or quasi-experiments could examine how early warning alerts change buyer behavior, and whether the safeguards proposed here prevent alerts from accelerating the failures they are meant to anticipate.

10. Conclusion

Supplier financial distress is a slow-moving but high-consequence threat to supply chain continuity. The evidence needed to detect it is usually present inside the buying organization, but it is scattered across functions and rarely combined. This paper has proposed an integrated early warning framework that brings together financial indicators, delivery performance, payment behavior and concentration risk; separates the likelihood of distress from the impact of failure; adjusts for deterioration momentum; escalates on hard triggers; and links every score to a defined response. The stylized application shows how such a framework can surface distress from transactional and operational data months before it appears in financial statements, and how impact weighting focuses attention on the suppliers whose failure would matter most. Empirical testing of the propositions advanced here, using linked supplier performance, payment and outcome data, is the natural next step, and offers a promising route toward supply chains that are not only more resilient to shocks but better at seeing them coming.

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