

Artificial Intelligence for Coupled Financial and Logistics Risk Management in Supply Chains

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ABSTRACT

Supply chains move goods and money together, yet firms, lenders and logistics providers still manage the two flows with separate models, separate data and separate risk owners. A delayed vessel lengthens the cash conversion cycle, a stretched cash cycle raises a supplier's default probability, and a supplier default removes physical capacity from the network. Artificial intelligence now forecasts each of these events well in isolation, but the coupling between them is rarely modelled. This paper reviews the literature at the intersection of financial risk, logistics and artificial intelligence, drawing on a structured corpus of peer-reviewed studies, regulatory frameworks and recent work up to early 2026. The review organises the evidence into five method families: credit and default prediction, disruption and freight market forecasting, network learning, language models for unstructured risk signals, and prescriptive decision models. It finds that each family is mature on its own side of the boundary and thin across it. On this basis the paper proposes the Coupled Flow Risk framework, a five-layer architecture of sensing, prediction, propagation, prescription and governance, with a formal coupling term that lets logistics stress enter credit risk and credit stress enter logistics capacity, and a decision rule that trades expected cost against conditional value-at-risk. The paper closes with a research agenda on calibration, causal validation, fair access to supply chain finance and model risk governance.

Keywords: supply chain finance; logistics risk; artificial intelligence; credit risk; machine learning; conditional value-at-risk; supply chain resilience

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INTRODUCTION

A supply chain carries two flows at once. Goods move downstream from supplier to carrier, port, warehouse and buyer, and money moves upstream as invoices, receivables, payables, credit lines and settlements. The two flows are managed by different professions: logisticians and operations planners own the first, while treasurers, credit officers and banks own the second. The division made sense when the flows could be treated as loosely linked, but the evidence of the past two decades shows that they are tightly bound. Hendricks and Singhal (2003) found that announcements of supply chain glitches were followed by an average abnormal shareholder loss of about ten percent, and their later study showed that disruptions depress stock returns and raise equity risk for years afterwards (Hendricks and Singhal, 2005). The COVID-19 pandemic and the container shipping crisis that followed made the same point at global scale, as port congestion and freight rate spikes fed directly into working capital strain and trade credit stress (Notteboom et al., 2021; Queiroz et al., 2022).

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Artificial intelligence (AI) has advanced rapidly on both sides of this boundary. In logistics and operations, machine learning (ML) now supports demand forecasting, disruption prediction, supplier risk scoring and inventory control (Baryannis et al., 2019; Pournader et al., 2021; Toorajipour et al., 2021). In finance, gradient-boosted trees, neural networks and explainable ML have become standard tools for credit scoring and default prediction (Lessmann et al., 2015; Barboza et al., 2017; Bussmann et al., 2021). Applied work in emerging

markets has followed both paths, proposing predictive models for demand forecasting and procurement planning alongside machine learning for fraud detection and anti-money laundering in banking (Aifuwa et al., 2020; Okonkwo et al., 2024c; Atakpa, 2021; Atakpa and Abetoh, 2022). Supply chain finance (SCF) sits between the two and has attracted its own stream of ML work on small and medium-sized enterprise (SME) credit risk (Zhu et al., 2017, 2019; Hou et al., 2024). Yet the reviews that map these streams tend to stay on one side. Reviews of AI in supply chain risk management rarely treat default risk as an outcome, and reviews of ML in credit risk rarely treat shipment delay, freight cost or network position as inputs (Ni et al., 2020; Riahi et al., 2021).

This paper addresses that gap. Its purpose is to review what AI contributes when financial risk and logistics risk are treated as one coupled system, and to propose a framework that makes the coupling explicit. Three questions guide the review. The first asks which AI method families have been applied to financial risk and to logistics risk in supply chains, and with what evidence. The second asks where the literature models the transmission of risk between the physical flow and the financial flow, and where it does not. The third asks what architecture, formal model and governance arrangement would allow an organisation to manage the coupled risk with AI while remaining accountable to regulators and counterparties. These questions follow the operations-finance interface tradition, which argues that operational and financial decisions must be optimised jointly rather than in sequence (Birge, 2015; Zhao and Huchzermeier, 2015).

The paper makes three contributions. First, it consolidates evidence from supply chain risk management, supply chain finance, credit risk modelling, freight market forecasting and AI governance into a single taxonomy of method families and coupling channels. Second, it proposes the Coupled Flow Risk (CFR) framework, which links a sensing layer, a probabilistic prediction layer, a network propagation layer, a risk-aware prescription layer and a governance layer, and which formalises the coupling through a shared default model and a conditional value-at-risk objective (Rockafellar and Uryasev, 2000). Third, it sets out a research agenda that gives priority to calibration, causal validation, equitable access to finance and model risk management (Board of Governors of the Federal Reserve System and Office of the Comptroller of the Currency, 2011; NIST, 2023). The remainder of the paper presents the conceptual foundations in Section 2, the review method in Section 3, the method families in Section 4, the CFR framework in Section 5, the discussion and agenda in Section 6, and the conclusion in Section 7.

CONCEPTUAL FOUNDATIONS

The conceptual foundations of this review come from three bodies of work that have seldom been read together. The first is supply chain risk management, which explains how disruptions arise and spread through physical networks. The second is the operations-finance interface, which explains

why production, inventory and financing decisions interact. The third is the economics of production networks, which shows that shocks to individual firms travel along supplier and customer links and can move prices and aggregate output. Each tradition supplies part of the coupled picture, and each has been reviewed separately (Sodhi et al., 2012; Zhao and Huchzermeier, 2015; Acemoglu et al., 2012). This section draws them into a single account of how logistics risk and financial risk meet.

Logistics risk and the ripple effect

Supply chain risk management grew out of the recognition that lean, globally dispersed networks trade resilience for efficiency. Early work classified risks by source, distinguishing supply, demand, process and environmental risks, and argued that firms must treat disruption as a design parameter rather than an exception (Christopher and Peck, 2004; Jüttner, 2005; Kleindorfer and Saad, 2005). Tang (2006) reviewed the quantitative models then available and showed how robust strategies such as postponement, flexible supply contracts and strategic inventory can cut vulnerability at modest cost. Later reviews confirmed that the field had become broad but uneven, with strong coverage of supplier selection and inventory buffers and weaker coverage of risk measurement and multi-tier visibility (Ho et al., 2015; Fahimnia et al., 2015; Heckmann et al., 2015). Sector studies show why visibility matters: in engineering, procurement and construction projects and gas processing plants, a single late critical item can stop production, so risk and resilience frameworks for these settings emphasise end-to-end traceability, secure data flows and resilience indices that can be tracked over time (Agbabiaka et al., 2019; Ogunwole et al., 2021; Okonkwo et al., 2024b; Nnabueze et al., 2021; Efobi et al., 2023a). Lean practices sharpen the problem further, since removing buffers raises efficiency but also raises exposure when a single flow is interrupted (Ike et al., 2022). Procurement studies from oil, gas and energy facilities trace the same exposure to inventory availability, materials readiness, contract and vendor governance, and regulatory compliance in high-risk settings (Okonkwo et al., 2018a, 2018b, 2021a, 2019, 2021b), and reviews of force majeure clauses show how contractual terms determine who bears the cost when an energy supply chain is disrupted (Ngonadi et al., 2020). Pharmaceutical supply chains provide a sharper case still, because a stock-out is a public health failure: resilience strategies, sustainable procurement frameworks, drug shortage early warning models and governance of environmental risk have all been proposed for this sector (Awulu et al., 2022; Akinleye, 2024; Eze et al., 2022, 2023).

The concept that best captures modern logistics risk is the ripple effect, which describes how a disruption at one node propagates downstream and upstream through a network, altering capacity, lead times and costs well beyond the point of origin (Dolgui and Ivanov, 2021). Simulation studies of the COVID-19 outbreak showed that the timing of facility closures



and reopenings shaped network performance more than the length of any single closure (Ivanov, 2020). Ivanov and Dolgui (2020) extended the resilience argument to viability, the ability of intertwined supply networks to survive long disruptions by structural adaptation. Quantitative reviews of resilience analysis show that optimisation, simulation and Bayesian network methods dominate this literature, and that most models measure disruption impact in physical or cost units rather than in terms of credit or liquidity consequences (Hosseini et al., 2019). This omission is the first point of contact with the financial risk literature.

Financial risk in supply chains and the operations-finance interface

On the financial side, the central idea is that supply chains are also chains of credit. Petersen and Rajan (1997) documented that trade credit is one of the largest sources of short-term finance for firms, and that suppliers extend it partly because they hold information about buyers that banks lack. Supply chain finance generalises this insight into a set of instruments, including reverse factoring, dynamic discounting, inventory finance and purchase-order finance, that use the relationship between trading partners to lower financing costs (Gomm, 2010; Gelsomino et al., 2016; Xu et al., 2018). Empirical work shows that financial supply chain management depends on the same coordination capabilities as physical supply chain management (Wuttke et al., 2013), and that the benefits of SCF depend on who initiates the programme and how risk is shared among the buyer, the supplier and the financial institution (Caniato et al., 2016). Product design work for emerging-market banks extends the same idea to distributorship and trade finance, where lending is

secured by a distribution relationship rather than by fixed collateral (Agboada et al., 2018), and treasury architectures for multinational firms show how cash flow consolidation and foreign exchange control depend on the timing of cross-border operational flows (Dada et al., 2021a). Customer relationship data are already used to forecast credit demand across the channels of lending institutions (Dada et al., 2021b), and post-pandemic collaboration models for banks and capital markets show that financial resilience depends on how quickly the real economy recovers (Isiekwu et al., 2025). Relationship banking performs the same function inside a lender's portfolio, where knowledge of a client's operations supports growth and profitability (Ezeako et al., 2019). Enterprise finance research adds the reporting, planning and control systems through which such exposures are recognized, from strategic accounting systems and financial reporting models to data-driven cost management, financial planning and executive decision systems (Bola-Sadipe et al., 2019; Medon and Oduleye, 2022; Oduleye and Medon, 2021; Medon and Oduleye, 2023; Lawal and Oduleye, 2019; Oduleye and Medon, 2023). Tax governance analytics for cross-border compliance, integrated data management for forecasting accuracy, and executive dashboards and capital efficiency models complete the toolkit that a treasury would bring to a coupled risk model (Lawal and Oduleye, 2018; Agu et al., 2023b; Walawalkar et al., 2025a, 2025b).

Operations research has formalised these links. Buzacott and Zhang (2004) showed that when inventory is financed against asset-based credit limits, the optimal production plan depends on the borrowing base, so operational and financing decisions cannot be separated. Kouvelis and Zhao (2012) analysed the capital-constrained newsvendor and

Table 1: Taxonomy of AI method families at the intersection of financial risk and logistics.

<i>Method family</i>	<i>Typical inputs</i>	<i>Risk outputs</i>	<i>Representative studies</i>	<i>Coupling channel covered</i>
Credit and default prediction	Financial ratios, payment history, SCF transaction data, core-enterprise attributes	Probability of default, credit grade, distress warning	Zhu et al. (2017, 2019); Hou et al. (2024); Wang et al. (2026)	Liquidity (partial); logistics inputs rarely used
Disruption, delay and freight forecasting	Supplier delivery records, ERP and TMS data, freight indices, external uncertainty factors	Delay probability, disruption likelihood, freight rate paths	Brintrup et al. (2020); Wang et al. (2025); Tonoyan et al. (2024a)	Liquidity (implicit); financial outcomes rarely modelled
Network learning	Supplier and customer links, knowledge graphs, transaction networks	Hidden links, node risk, propagated credit risk	Kosasih and Brintrup (2022, 2025); Liu et al. (2025)	Network (strong)
Language models and text mining	News, disclosures, site-visit transcripts, contracts	Supply chain maps, firm-level risk exposure scores	Wichmann et al. (2020); Fan et al. (2025); Fang et al. (2026)	Information (strong)
Prescriptive and reinforcement learning	Forecasts, costs, constraints, contract terms	Order, routing and financing decisions	Bertsimas and Kallus (2020); Gijsbrechts et al. (2022); Kouvelis and Zhao (2012)	Liquidity and network (weak, mostly single-sided)

found that supplier trade credit can dominate bank credit when the supplier prices default risk into the contract. Tunca and Zhu (2018) showed that a large buyer who intermediates supplier finance can lower supplier default and raise channel efficiency. Reviews of this operations-finance interface conclude that joint models consistently outperform sequential ones, but that most assume known distributions and do not exploit data-driven learning (Birge, 2015; Zhao and Huchzermeier, 2015). Moretto et al. (2019) argued for supply chain credit rating, in which a firm's creditworthiness is assessed in light of its position in a supply chain rather than from its balance sheet alone, which is precisely the move that AI can operationalise.

The coupling of physical and financial flows

The two flows meet at identifiable points. The most direct is the cash conversion cycle, which adds days of inventory outstanding to days of sales outstanding and subtracts days of payables outstanding. Every logistics delay extends inventory days or receivable days and so raises the working capital a firm must finance (Hofmann and Kotzab, 2010). Protopappa-Sieke and Seifert (2010) showed that inventory policies that look optimal on cost can look poor once their effect on working capital and payment terms is priced. Variance analytics for cost control in manufacturing firms make the same operational drivers visible in financial reporting (Aliliele et al., 2024). Profitability analysis in retail procurement, comparative studies of procurement cost optimization and machine learning models for predictive cost optimization and demand-driven revenue projection make the link explicit at the level of the purchase order (Akin-Oluyomi et al., 2020; Akokodaripon et al., 2023; Tonoyan et al., 2022, 2021), and localized supply chain models show that shortening physical flows can also stabilize local economic activity (Anene and Clement, 2024). Route optimisation models make the link explicit at the level of individual deliveries, treating logistics cost as a direct driver of delivery profitability (Tonoyan et al., 2025), while predictive financial forecasting and scenario-based financial models show how such operational drivers can be carried into corporate plans (Medon and Oduleye, 2024; Filani et al., 2023). A second meeting point is the network itself. Barrot and Sauvagnat (2016) found that natural disasters hitting a supplier depress the sales and market value of its customers when inputs are specific, and Carvalho et al. (2021) traced the output losses of the Great East Japan Earthquake through supplier and customer links far from the affected region. At the macroeconomic level, Acemoglu et al. (2012) showed that shocks to central sectors in the input-output network do not average out, so network structure itself generates aggregate risk.

Financial markets price these links, although slowly. Cohen and Frazzini (2008) showed that news about a customer predicts the returns of its suppliers with a lag, which implies that investors underreact to information that travels along supply links. Chod et al. (2020) showed that verifiable

transparency about a supplier's operations, for instance through blockchain records, lowers its financing costs because lenders can distinguish good operators from poor ones. Taken together, these studies define three coupling channels that an AI system must represent: a liquidity channel through the cash conversion cycle, a network channel through supplier and customer dependence, and an information channel through the signals that logistics data provide to lenders and investors. The review that follows is organised to test how well current AI methods cover each channel (Choi et al., 2018; Hendricks and Singhal, 2005).

REVIEW METHOD

The review follows a structured narrative design, which suits a field that spans several disciplines with different publication norms and where the aim is conceptual integration rather than effect-size pooling (Fahimnia et al., 2015; Ho et al., 2015). The corpus was assembled in four passes. The first pass identified anchor reviews in supply chain risk management, supply chain finance, AI in operations and ML in credit risk (Baryannis et al., 2019; Toorajipour et al., 2021; Xu et al., 2018; Lessmann et al., 2015). The second pass traced backward and forward citations from those anchors to reach primary empirical and methodological studies. The third pass searched bibliographic metadata for studies published from 2024 to early 2026 that combine ML with supply chain credit risk, freight markets, network risk or language models. The fourth pass added the regulatory and standards documents that govern the deployment of AI and models in financial institutions (NIST, 2023; European Parliament and Council of the European Union, 2024).

Four inclusion criteria were applied. A study had to be peer reviewed or be an official regulatory or standards publication; it had to address financial risk, logistics risk or their interaction in a supply chain or production network setting; it had to use, evaluate or inform the design of a data-driven or AI method, or supply the theoretical foundation that such a method requires; and its bibliographic record had to be verifiable through its digital object identifier or the issuing body. Preprints and non-reviewed working papers were excluded. Each retained work was coded on five attributes: the risk outcome it models, the side of the boundary its inputs come from, the method family, whether it represents a coupling channel, and the form of uncertainty it reports. The coded corpus underpins the taxonomy in Table 1 and the coupling analysis in Table 2. The design follows the practice of recent AI reviews in operations management that combine a structured corpus with an explicit analytical framework (Pournader et al., 2021; Rolf et al., 2023).

AI Methods Across the Coupled Risk Domain

This section reviews five method families. Table 1 summarises each family by its typical inputs, outputs, representative studies and the coupling channel it covers, and the subsections below discuss the evidence in each row. The



grouping follows the functional logic of an AI pipeline rather than the algorithms themselves, since the same algorithm, for example a gradient-boosted tree, appears in credit scoring, delay prediction and freight forecasting (Chen and Guestrin, 2016; Pournader et al., 2021). Grouping by function makes it possible to ask, for each family, which side of the boundary its inputs and outputs come from. Earlier reviews of AI in supply chains classified work by algorithm or by supply chain process (Toorajipour et al., 2021; Riahi et al., 2021), and reviews of deep learning in business analytics classified it by application domain (Kraus et al., 2020); neither scheme exposes the coupling that is the subject of this paper.

Credit and default prediction for supply chain actors

Credit risk modelling has the longest history of the five families. Altman (1968) introduced discriminant analysis on financial ratios, and the Z-score it produced remained a benchmark for decades. Barboza et al. (2017) re-ran the bankruptcy prediction problem with modern learners and found that bagging, boosting and random forests improved accuracy by roughly ten percentage points over discriminant and logistic models. The large benchmark by Lessmann et al. (2015) compared forty-one classifiers on eight credit scoring data sets and recommended heterogeneous ensembles as the new standard, a conclusion consistent with the strong performance of random forests and gradient boosting in general tabular prediction (Breiman, 2001; Chen and Guestrin, 2016). Khandani et al. (2010) showed with bank transaction data that ML forecasts of consumer delinquency could cut losses by six to twenty-five percent, which established the value of behavioural and transactional features over static ratios.

In supply chain finance, the key innovation is to use the relationship with a core enterprise as a source of information about a smaller supplier. Zhu et al. (2017) compared individual, ensemble and integrated ensemble learners for predicting SME credit risk in Chinese SCF and found that integrated ensembles performed best, and Zhu et al. (2019) improved on this with a hybrid ensemble that combines random subspace and multiboosting. Mou et al. (2018) built a credit evaluation model around core enterprise attributes, and Hou et al. (2024) combined recursive feature selection, class resampling and ML classifiers, reporting that the SME's own characteristics carry most of the predictive weight. Wang et al. (2026) developed an early warning system for listed service-oriented firms in China in which XGBoost with synthetic minority oversampling reached an F1 score of 0.950 and supply chain variables were significant predictors of distress. Olan et al. (2022) showed in the food and drink industry that AI networks can support sustainable SCF by improving information flow among partners. A parallel banking literature applies ML to fraud detection, anti-money laundering and anomaly detection in transaction and financial time-series data (Atakpa, 2021; Atakpa and Abetoh,

2022, 2023; Fadayomi et al., 2024; Hammed et al., 2026), to investment risk monitoring for SME fintech firms and private capital (Eboh and Aliliele, 2024, 2025b), and to predictive financial risk assessment and compliance analytics in financial institutions and public systems (Agu et al., 2025; Akomolafe et al., 2025a; Adelanwa et al., 2023b). Related frameworks address portfolio risk and due diligence against investment fraud (Eboh and Aliliele, 2023, 2025a), artificial intelligence support for financial crime investigation and regulatory technology for fraud reporting (Okoruwa et al., 2025b; Bello et al., 2025b), cyber risk management in financial institutions (Bello et al., 2024), blockchain-based know-your-customer and anti-money laundering controls (Bello et al., 2025a), comparative anti-money laundering regimes (Ominyi and Anichukwueze, 2021), and AI-assisted compliance monitoring with anomaly detection in high-volume transactions (Ominyi et al., 2024). Risk-based business intelligence for fintech platforms and audit analytics for financial oversight extend the same methods to assurance (Mbonu et al., 2021; Abetoh and Atakpa, 2024; Ozowara et al., 2025), building on earlier models of technology-enabled internal audit, risk-based internal control, risk-based auditing and compliance risk in emerging economies (Akomolafe and Agu, 2018, 2019; Akomolafe et al., 2023a, 2023b), together with SOX compliance and AI-enabled IT general controls (Agu et al., 2023a; Mbonu et al., 2022) and evidence on how cognitive biases distort audit and risk judgments (Fobellah, 2025a). Machine learning has also reshaped insurance underwriting (Oluwo et al., 2024), and frameworks for analytics-driven decision making in banks and for financial governance in small and medium enterprises describe the organizational conditions under which these models are used (Oluwo et al., 2025; Eboh et al., 2025).

Two limits recur in this family. The first is that logistics variables are almost never used as features. This holds for the SCF studies and for the banking fraud and risk studies alike, whose features describe transactions, accounts and firms rather than shipments. The models draw on balance sheets, payment histories and core enterprise ratings, but not on on-time delivery rates, shipment dwell times or exposure to congested lanes, even though those variables move before the balance sheet does. The second limit is that the outputs are point scores rather than calibrated probabilities with stated uncertainty, which matters because SCF pricing and limits depend on the level of default probability, not only on its rank (Bussmann et al., 2021; Fuster et al., 2022). The CFR framework in Section 5 addresses both limits directly.

Disruption, delay and freight market forecasting

The second family predicts events in the physical flow. Carbonneau et al. (2008) showed early that neural networks and support vector machines could forecast distorted demand signals in extended supply chains better than naive methods, and the M5 competition later confirmed that

gradient-boosted trees and global neural models dominate large-scale retail demand forecasting (Makridakis et al., 2022). Probabilistic deep learning, such as the autoregressive recurrent model DeepAR and the Temporal Fusion Transformer, now produces full predictive distributions and interpretable attention weights across many related series (Salinas et al., 2020; Lim et al., 2021), building on the long short-term memory architecture (Hochreiter and Schmidhuber, 1997). These are the right tools for forecasting quantities that enter a financial model, because a treasury decision needs a distribution of possible cash outcomes, not a single forecast.

For disruption and delay, Brintrup et al. (2020) used purchase order data from a complex asset manufacturer to predict late supplier deliveries and showed that features engineered from order history carried most of the signal. Simchi-Levi et al. (2015) developed a risk exposure index for Ford's supply network based on time-to-recover, which ranks suppliers by the financial impact of their failure rather than by spend, an early and influential bridge between the two flows. Recent work extends supplier-level prediction to vendor management practices and their measurable effect on supply chain performance (Wedraogo et al., 2025). Applied models from emerging economies cover predictive procurement planning, e-commerce demand forecasting, warehouse path planning with autonomous mobile robots, reverse logistics and queueing-based throughput analysis (Okonkwo et al., 2024c; Akin-Oluyomi et al., 2023c; Akanbi and Sunday, 2024; Anene et al., 2025; Adesanya et al., 2024), and vendor and procurement risk models that score suppliers and sourcing exposure before disruption occurs (Tonoyan et al., 2024a; Bello et al., 2023; Akin-Oluyomi et al., 2023b; Nwangwu et al., 2025). A large applied literature supplies the procurement data on which such models depend, including process automation, supplier relationship management and big data analytics in procurement (Akinleye and Adeyoyin, 2021, 2022; Akinleye et al., 2023), green and cross-border supplier management and supplier sustainability metrics (Akin-Oluyomi et al., 2023a, 2024, 2023d), business intelligence and visualization for vendor performance (Abdulrazaq et al., 2025; Babatope et al., 2023), and geospatial vendor evaluation and GIS-enabled ERP procurement (Ahiaeke Patrick et al., 2021, 2020). Supply chain analytics frameworks for forecasting accuracy and bottleneck reduction, leadership and governance models that align logistics decisions with enterprise strategy, and multi-site performance indicators complete this picture (Akin-Oluyomi and Akhigbe, 2023b, 2023a, 2022, 2023c), while reviews of throughput optimization, Lean Six Sigma in pharmacy distribution, cold chain integrity and risk-based import compliance show how the same analytics apply to specific logistics flows (Nwangwu et al., 2024; Obukadata et al., 2021; Aneke and Adesemoye, 2025, 2021). Integrated AI and predictive analytics frameworks for supply chain management and AI-based predictive maintenance for e-commerce systems carry these methods into operations

(Rukh et al., 2024; Mayo et al., 2023). Predictive analytics and Internet of Things sensing have also been combined for humanitarian logistics, where delivery failure has direct social cost (Anene and Clement, 2022). In maritime logistics, neural networks have become common tools for freight rate forecasting, and an interpretable multi-model ensemble has been proposed that forecasts ocean freight indices using external uncertainty factors (Wang et al., 2025). Freight rates are a financial variable produced by a logistics market, so this sub-literature is already a coupling point, although it seldom links the forecast to the credit exposure of the shippers and carriers who bear the rate risk.

Network learning and risk propagation

The third family treats the supply chain as a graph. Supply chains are only partly visible to any one firm, since a buyer typically knows its direct suppliers but not their suppliers. Kosasih and Brintrup (2022) used graph neural networks to predict hidden links in an automotive network, and their later neurosymbolic approach combined learned embeddings with logical rules over a supply chain knowledge graph to make link predictions more trustworthy (Kosasih and Brintrup, 2025). Brintrup et al. (2024) framed these methods as digital supply chain surveillance, the AI-enabled monitoring of a network beyond the first tier, and they set out both its benefits and risks, including the possibility that inferred links are wrong or that surveillance raises confidentiality concerns among suppliers. Supplier relationship management and digital supply chain governance frameworks provide the organisational counterpart to these methods, since the willingness of partners to share data determines how much of the network can be observed (Ike et al., 2021; Okonkwo et al., 2024a). The enabling infrastructure includes service-management automation, the integration of IT systems engineering with supply chain operations, asset lifecycle and inventory visibility models, and digital procurement platforms that make transactions transparent across partners (Okonkwo et al., 2024f, 2023a, 2023b; Okoruwa et al., 2024, 2025a). Security and governance of this infrastructure matter as well: attribute-based encryption for smart supply chains, IT risk and ISO controls embedded in agile supply chain transformation, and shared-responsibility models for multi-jurisdictional supply chain governance all shape which links a network model can safely observe (Shittu and Nabil, 2023; Mbonu et al., 2020; Ominyi et al., 2021).

On the finance side, Liu et al. (2025) proposed a modified graph attention network with contrastive learning to assess supply chain financial risk, capturing higher-order dependencies and the transmission of credit risk along long chains. This work is important because it is one of few studies that places credit risk on the edges of a supply network rather than on isolated nodes. The economic evidence reviewed in Section 2.3 supports this design: shocks propagate through input specificity and network centrality (Acemoglu et al., 2012; Barrot and Sauvagnat, 2016). Yet network models in the



finance stream typically use transaction or guarantee links and ignore logistics links such as shared carriers, ports and lanes, which are exactly the paths through which a physical shock reaches many firms at once (Notteboom et al., 2021). The CFR framework therefore defines a single graph whose nodes include lenders and logistics providers as well as buyers and suppliers.

Language models and unstructured risk signals

The fourth family extracts risk signals from text. Wichmann et al. (2020) trained deep neural networks to extract buyer and supplier relations from news articles, producing supply chain maps that no single firm could assemble from its own records. The arrival of large language models (LLMs) has widened this capability. Fan et al. (2025) used a generative LLM to read site-visit transcripts of Chinese listed firms and construct a firm-level measure of supply chain risk, which was associated with higher cost of capital, higher stock volatility and larger inventory holdings. Fang et al. (2026) built an LLM framework that identifies technology-driven supply chain risks in corporate disclosures, and they reported that the LLM-derived measures explain ten to fifteen percent more variance than traditional text methods. Jackson et al. (2024) mapped generative AI capabilities in supply chain and operations management and noted their strength in synthesis and scenario generation as well as their tendency to produce plausible but false content. In trade, AI has been applied to customs declarations and trade facilitation to flag risky consignments (Jones and Ominyi, 2024b) and proposed as an advisory layer that extends trade compliance expertise to small exporters (Jones and Ominyi, 2025), and agentic orchestration of multi-enterprise supply chain data has been framed with explicit process guardrails (Ogundairo, 2025). Natural language processing has also been applied to detect regulatory liabilities in high-volume contracts and to score contracts before negotiation (Ngonadi et al., 2025b; Uzougbo et al., 2024), AI has been used to synthesize stakeholder and survey data in operations research (Obukadata et al., 2024), and harmonized digital trade rules shape what text and transaction data cross-border e-commerce can share (Jones and Ominyi, 2024a).

For the coupled problem, the text channel is valuable because it moves early. Strike notices, port advisories, regulatory announcements, earnings call remarks and customs rule changes appear in text days or weeks before they appear in delivery data or financial statements. The evidence of Cohen and Frazzini (2008) that markets underreact to information travelling along supply links suggests that timely extraction of such signals has economic value. The risk is that LLM outputs are unverified and hard to audit, which is why the CFR framework treats language models as sensors whose outputs enter the prediction layer as features with recorded provenance, rather than as decision makers.

From prediction to prescription

The fifth family turns forecasts into decisions. The predict-then-optimize paradigm has been sharpened by work showing that learning should be aligned with the downstream decision. Bertsimas and Kallus (2020) introduced prescriptive analytics that weight historical observations by their similarity to the current context, and Elmachtoub and Grigas (2022) trained predictive models against the decision loss rather than the forecast error. Ban and Rudin (2019) showed that a data-driven newsvendor using features can beat classical estimate-then-optimize approaches. Reinforcement learning (RL) is the other main route. Oroojlooyjadid et al. (2022) applied a deep Q-network to the beer game, and Gijbrecchts et al. (2022) showed that deep RL can match strong heuristics on lost-sales, dual-sourcing and multi-echelon inventory problems, although it requires careful tuning; the broader review by Rolf et al. (2023) confirms that RL in supply chains is promising but mostly tested in simulation. At the enterprise level, integrated IT and procurement systems, enterprise resource planning adoption and digital cost-control models supply the transactional data and execution channels through which any prescriptive model must act (Okonkwo et al., 2024d, 2024e, 2025). Digital twins and automation that reduce procurement errors and support environmental compliance (Akinlade et al., 2024; Ike et al., 2025), lifecycle performance management in infrastructure delivery (Adelanwa et al., 2023a), quantitative risk allocation in public-private partnerships (Ike et al., 2024), and frameworks for AI in strategic business decisions and for AI adoption readiness in small firms (Shah et al., 2025; Alieme et al., 2023) describe the organizational side of prescription.

The gap here is that the objectives are single-sided. Inventory and routing models minimise expected operational cost, and credit models maximise risk-adjusted return, but few models let an inventory decision be penalised for the default risk it creates or let a financing decision be informed by the delay risk it absorbs. The capital-constrained newsvendor literature shows that the joint problem is tractable when distributions are known (Buzacott and Zhang, 2004; Kouvelis and Zhao, 2012). What is missing is a data-driven version that uses learned, calibrated distributions from both sides and a coherent risk measure such as conditional value-at-risk (Rockafellar and Uryasev, 2000; Sawik, 2011). Section 5 proposes such a formulation.

The Coupled Flow Risk Framework

The review in Section 4 shows that the components of a coupled system already exist: accurate credit models, probabilistic logistics forecasts, graph learners for multi-tier networks, language models that read early warnings, and decision models that optimise under uncertainty. What is missing is an architecture that connects them and a formal statement of how risk passes from one flow to the other. The Coupled Flow Risk framework supplies both. It builds on the digital supply chain twin, which already links data, models

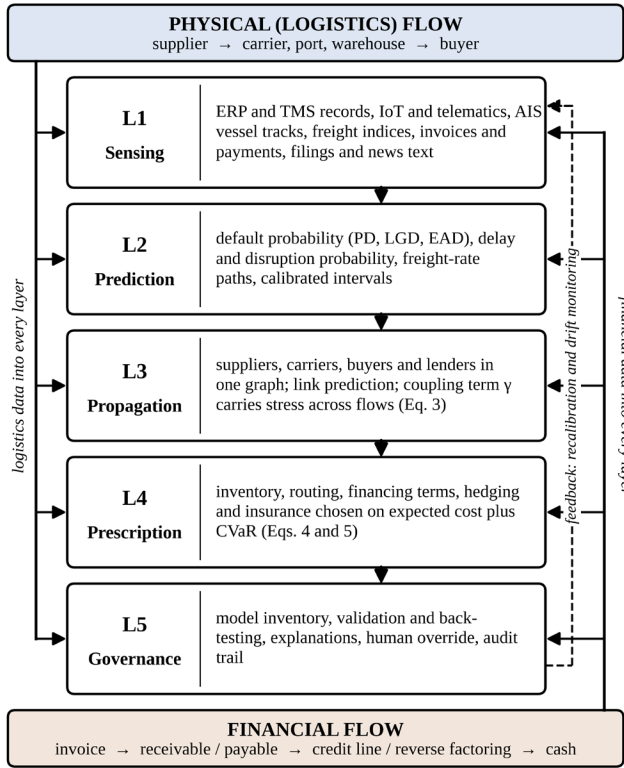


Figure 1: The Coupled Flow Risk (CFR) framework. Five AI layers sit between the physical flow and the financial flow; data from both flows enter every analytical layer, the coupling term transmits stress between the flows, and realised outcomes return to the sensing and prediction layers for recalibration.

and decisions in a closed loop for physical flows (Ivanov and Dolgui, 2021), and on supply chain credit rating, which already argues that creditworthiness depends on network position (Moretto et al., 2019). The framework extends both by placing the financial and physical flows inside one model.

5.1 Architecture

The CFR framework is shown in Figure 1. It consists of five layers placed between the physical flow and the financial flow. The sensing layer (L1) collects operational data from enterprise resource planning and transport management systems, telematics and vessel tracking, freight indices, invoices and payment records, and text from filings and news. The prediction layer (L2) produces calibrated probabilistic forecasts of default, delay, disruption and freight rates. The propagation layer (L3) represents buyers, suppliers, carriers, ports and lenders as one graph and transmits predicted stress across it. The prescription layer (L4) chooses inventory, routing, financing and hedging actions under a joint cost and risk objective. The governance layer (L5) maintains the model inventory, validation, explanation and audit functions required of models used in financial decisions (Board of Governors of the Federal Reserve System and

Office of the Comptroller of the Currency, 2011; NIST, 2023). A feedback path returns realised outcomes to the earlier layers for recalibration and drift monitoring, in the spirit of the digital supply chain twin (Ivanov and Dolgui, 2021). The architecture is consistent with recent proposals for enterprise financial analytics that embed AI across planning, reporting and control rather than confining it to single use cases (Walawalkar et al., 2026).

The design choices in Figure 1 respond to the gaps identified in Section 4. Every analytical layer takes data from both flows, which answers the finding that credit models ignore logistics features and logistics models ignore financial outcomes. The propagation layer puts lenders and logistics providers in the same graph, which answers the finding that network models in finance omit logistics links (Liu et al., 2025; Kosasih and Brintrup, 2022). The prescription layer uses a risk measure that can be computed from the joint distribution of operational and financial losses, which answers the finding that decision models are single-sided. The governance layer is a full layer rather than an afterthought, because high-stakes decisions about credit call for models that can be explained and validated (Rudin, 2019; European Parliament and Council of the European Union, 2024).

Formal coupling of logistics and credit risk

The liquidity channel is represented through the cash conversion cycle of firm i at time t :

$$CCC_{i,t} = DIO_{i,t} + DSO_{i,t} - DPO_{i,t} \quad (1)$$

where DIO, DSO and DPO are days of inventory, sales and payables outstanding. A logistics delay raises DIO for the consignee and DSO for the shipper, and the extra days must be financed (Hofmann and Kotzab, 2010). The credit loss that a lender or a buyer-led SCF programme expects from exposure to firm i follows the standard decomposition

$$EL_{i,t} = PD_{i,t} \times LGD_{i,t} \times EAD_{i,t} \quad (2)$$

where PD is the probability of default, LGD the loss given default and EAD the exposure at default (Bussmann et al., 2021). The CFR framework makes PD a function of both the firm's own features and the logistics stress of its neighbours in the supply graph:

$$PD_{i,t} = \sigma \left(\beta_0 + \hat{\mathbf{a}}^\top \mathbf{x}_{i,t} + \gamma \sum_{j \in \mathcal{N}(i)} w_{ij} d_{j,t} \right) \quad (3)$$

where σ is the logistic link, $\mathbf{x}_{i,t}$ contains financial, payment and firm-level logistics features, $\mathcal{N}(i)$ is the set of graph neighbours of i (suppliers, customers, carriers and ports), w_{ij} is a dependence weight learned by the propagation layer, and $d_{j,t}$ is the predicted disruption or delay probability of neighbour j . The coefficient γ is the coupling term. When $\gamma = 0$ the model collapses to a conventional credit score; a



Table 2: Coupling channels between the physical and financial flows and their representation in the CFR framework

<i>Coupling channel</i>	<i>Mechanism</i>	<i>Supporting evidence</i>	<i>CFR representation</i>
Liquidity	Delays extend inventory and receivable days and raise financing needs	Hofmann and Kotzab (2010); Protopappa-Sieke and Seifert (2010)	CCC in Eq. (1) as a feature of PD; financing cost in C of Eq. (5)
Network	Shocks travel along specific supplier, customer and logistics links	Barrot and Sauvagnat (2016); Carvalho et al. (2021); Acemoglu et al. (2012)	Neighbour term with weights w and coupling coefficient in Eq. (3)
Information	Logistics and text signals reveal credit quality before financial statements	Cohen and Frazzini (2008); Chod et al. (2020); Fan et al. (2025)	Text and tracking features in L1 with provenance, entering L2
Price	Freight rate and input price shocks transfer margin risk between shippers and carriers	Notteboom et al. (2021); Wang et al. (2025)	Freight path scenarios in the joint scenario of Eq. (5); hedging actions in the decision set
Market valuation	Disruptions reduce equity value and raise equity risk	Hendricks and Singhal (2003, 2005)	Optional equity-implied PD input to L2; tail loss in CVaR

positive and significant γ is an empirical statement that logistics stress transmits into credit risk. In practice the linear index in Eq. (3) can be replaced by a gradient-boosted or graph neural model, but keeping an interpretable coupling term has value for validation and supervisory review (Rudin, 2019; Lessmann et al., 2015). The reverse channel, in which a supplier's rising PD reduces its expected delivery capacity, enters through $d_{j,a}$ in the next period, so the two flows are linked in both directions.

Risk-aware prescription

The prescription layer measures tail loss with conditional value-at-risk (CVaR), which for a loss L and confidence level α can be written in the variational form of Rockafellar and Uryasev (2000):

$$\text{CVaR}_\alpha(L) = \min_{\eta \in \mathbb{R}} \left(\eta + \frac{1}{1-\alpha} \mathbb{E}[\max(L - \eta, 0)] \right) \quad (4)$$

CVaR is coherent and convex in the decision when losses are convex, so it can be optimised with sample scenarios drawn from the prediction layer. The decision a , which may bundle order quantities, carrier and route choices, early payment discounts, credit limits and freight hedges, is then chosen as $\hat{a}$ by

$$\hat{a} = \arg \min_{a \in \mathcal{A}} \mathbb{E}_\xi [C(a, \xi)] + \lambda \text{CVaR}_\alpha(L_{\text{op}}(a, \xi) + L_{\text{cr}}(a, \xi)) \quad (5)$$

where ξ is the joint scenario of logistics and financial outcomes, C is the expected operating and financing cost, L_{op} and L_{cr} are the operational and credit losses, and $\lambda \geq 0$ sets the organisation's risk appetite. Summing the two losses inside a single CVaR, rather than constraining them separately, is what allows the model to see that a cheap slow route and a thin supplier credit line are dangerous together

even if each is acceptable alone. The formulation generalises the disruption-aware supply portfolio model of Sawik (2011) and the capital-constrained newsvendor (Kouvelis and Zhao, 2012), and it can be trained in the decision-focused manner of Elmachtoub and Grigas (2022). In practice the expectation and the CVaR in Eq. (5) are estimated from a finite set of joint scenarios sampled from the prediction layer, which turns the problem into a linear or mixed-integer programme when costs and losses are piecewise linear (Rockafellar and Uryasev, 2000). The value of λ should be set with the treasury and credit functions, not by the logistics team alone, because it expresses the organisation's appetite for combined loss. Table 2 shows how each coupling channel identified in Section 2.3 is represented in the framework.

DISCUSSION

The discussion considers what the review and the framework imply for practice and research. Four themes emerge. The first concerns the quality of the probabilities that a coupled model produces and the governance those probabilities require. The second concerns the data on which the model depends and the fairness of the decisions it supports. The third is a research agenda that follows from the gaps identified in Section 4. The fourth concerns the organisational and policy changes needed for firms, lenders and governments to benefit from coupled risk management. Each theme is grounded in the reviewed evidence and in the regulatory frameworks that already apply to AI and to model use in finance (NIST, 2023; Board of Governors of the Federal Reserve System and Office of the Comptroller of the Currency, 2011).

Calibration, explanation and model risk governance

The first implication of the review is that calibration matters more than ranking at the coupling point. A logistics team can

act on a ranked list of risky suppliers, but a credit decision sets a price and a limit that depend on the level of PD, and Eq. (5) weighs tail losses that are only meaningful if the underlying probabilities are well calibrated. Many of the ML studies reviewed report accuracy, area under the curve or F1 scores, which describe discrimination but say little about calibration (Zhu et al., 2019; Wang et al., 2026). Conformal prediction offers a distribution-free way to attach valid intervals to any learned model's outputs (Angelopoulos and Bates, 2023), and probabilistic forecasters such as DeepAR produce full distributions by design (Salinas et al., 2020). The CFR prediction layer should report both, and the governance layer should back-test them against realised defaults and delays.

Explanation is the second requirement. Post-hoc methods such as Shapley additive explanations are widely used in credit risk (Lundberg and Lee, 2017; Bussmann et al., 2021), but Rudin (2019) warns that explanations of black-box models can be unfaithful and argues for inherently interpretable models where decisions carry high stakes. The coupling coefficient in Eq. (3) is a small concession to this view: it keeps the most policy-relevant quantity visible even when the rest of the model is complex. Supervisory guidance requires that models used in financial decisions be inventoried, validated independently and monitored for performance drift (Board of Governors of the Federal Reserve System and Office of the Comptroller of the Currency, 2011). The NIST AI Risk Management Framework adds functions to govern, map, measure and manage AI risks (NIST, 2023), and the EU AI Act classifies AI systems used to evaluate the creditworthiness of natural persons as high risk (European Parliament and Council of the European Union, 2024). Audit practice is adapting in parallel, with conceptual work on auditing AI-powered financial systems (Fobellah, 2025b) and on automated evaluation and release-gating of models before deployment (Nwakamma et al., 2024). Reviews of algorithmic accountability and model risk management in financial services, responsible AI governance for automated decision systems, anti-discrimination compliance for automated decisions, and responsible AI in IT auditing with human oversight provide further guidance (Ominyi and Anichukwueze, 2023, 2024; Annan, 2025; Elebe and Anunagba, 2025), as do implementation pathways from periodic audit to continuous AI-enabled control, real-time compliance pipelines, and automated governance of multi-country delivery and distribution networks (Adebayo et al., 2025; Ngonadi et al., 2022, 2025a, 2023). The unintended costs of compliance obligations should also be weighed when new controls are designed (Fobellah, 2025c). Operational resilience principles for banks also expect institutions to map the third parties on which their critical operations depend, which in trade finance includes logistics providers (Basel Committee on Banking Supervision, 2021).

Data, fairness and access to finance

The value of AI at the coupling point depends on data that are spread across organisations that do not normally share

them. Carriers hold tracking data, buyers hold purchase order and delivery data, banks hold payment and credit data, and SMEs hold little that is machine readable at all. Digital platforms and distributed ledgers can make some of this data verifiable, and Chod et al. (2020) showed that verifiable transparency lowers financing costs for good suppliers. Saberi et al. (2019) noted, however, that blockchain adoption in supply chains faces technical, organisational and inter-organisational barriers. Payment infrastructure is a second route to machine-readable data. Smart contracts for supplier payment and dispute resolution, AI risk scoring of cross-border trade payments and predictive liquidity models for remittance flows all produce records that link a financial event to the physical transaction behind it (Akomolafe et al., 2022, 2023c, 2024b; Adesuyi et al., 2024). The same infrastructure carries its own risks, including fraud in international payment channels, correspondent banking exposure and disruption under geopolitical stress (Adesuyi et al., 2025a, 2025b; Okafor et al., 2024). Interoperability, gateway architecture, data-sharing governance, standardization, compliance redesign and the macroeconomic effects of distributed-ledger payments are all active questions (Adesuyi et al., 2023; Akomolafe et al., 2024a, 2025b, 2025c; Olaogun et al., 2023, 2025), and blockchain-based data exchange, tamper-proof recordkeeping, digital identity for financial inclusion and blockchain-enabled logistics management show how verifiable records can reach smaller participants (Kumuyi et al., 2023; Anichukwueze et al., 2021; Kumuyi et al., 2024; Ekwunife et al., 2024). Big data reviews in logistics similarly report that integration and data quality, rather than algorithms, are the binding constraints (Wang et al., 2016; Nguyen et al., 2018). The CFR framework therefore places provenance recording in L1 and assumes that each data source carries a quality flag that the prediction layer can use. Real-time risk dashboards built for hospital supply chains and regulatory supplier assessments in pharmaceutical procurement show that such flags can be operated in practice (Filani et al., 2022; Akin-Oluyomi et al., 2023b).

Fairness is the other side of data. Fuster et al. (2022) showed that more flexible ML credit models in US mortgage markets increased average accuracy but widened differences in outcomes across groups, because the models exploit nonlinear combinations of variables that correlate with group membership. In supply chains, the analogous risk is that SMEs in regions with poor logistics infrastructure will be scored as riskier because their shipments are slower, even when their own management is sound. Such a result may be statistically accurate and still self-reinforcing, since the higher financing cost further weakens the firm. SCF programmes were created in part to extend the buyer's credit quality to smaller suppliers (Gelsomino et al., 2016; Caniato et al., 2016), so an AI design that penalises infrastructure disadvantage would work against the purpose of the instrument. Monitoring of disparate impact across regions and firm sizes should therefore be part of L5.



Table 3: Research agenda for AI at the intersection of financial risk and logistics

<i>Research direction</i>	<i>Open question</i>	<i>Suggested approach</i>	<i>Anchoring studies</i>
Coupling estimation	Does logistics stress add predictive power for default beyond financial data?	Matched panels of delivery, freight and credit records; test of the coupling coefficient	Brintrup et al. (2020); Moretto et al. (2019)
Causal validation	Do interventions such as early payment or rerouting reduce default?	Natural experiments, difference-in-differences on disruption events	Barrot and Sauvagnat (2016); Carvalho et al. (2021)
Decision-focused learning	How should models be trained when losses span both flows?	Joint cost plus CVaR loss in smart predict-then-optimize	Elmachtoub and Grigas (2022); Rockafellar and Uryasev (2000)
Multi-tier graph risk	Can inferred links be trusted for credit decisions?	Neurosymbolic and graph attention models with link uncertainty	Kosasih and Brintrup (2025); Liu et al. (2025)
LLM risk sensing	Are LLM-derived risk scores stable, auditable and free of hallucinated events?	Provenance tracking, human validation samples, stability tests	Fang et al. (2026); Jackson et al. (2024)
Fair and governed deployment	Does coupled scoring disadvantage SMEs in weak logistics regions?	Disparate impact monitoring, interpretable coupling terms, model risk validation	Fuster et al. (2022); NIST (2023)

Research agenda

The review points to six research directions, set out in Table 3. The first is empirical estimation of the coupling term in Eq. (3) using matched logistics and credit panels, which would test whether logistics stress adds predictive power beyond financial ratios, as the evidence on supplier delivery prediction and supply chain credit rating suggests it should (Brintrup et al., 2020; Moretto et al., 2019). The second is causal validation. Most ML studies in this area are predictive, but managers and supervisors need to know whether an intervention such as early payment or rerouting will reduce default, which requires quasi-experimental designs of the kind used in the production network literature (Barrot and Sauvagnat, 2016; Carvalho et al., 2021). The third is decision-focused learning for the joint problem, extending the work of Elmachtoub and Grigas (2022) and Bertsimas and Kallus (2020) to objectives that combine operational and credit losses.

The fourth direction concerns trust in inferred multi-tier links. Link prediction can reveal hidden dependencies, but a credit decision based on a wrongly inferred link could harm a firm that has no such exposure, so the uncertainty of each inferred edge should propagate into the PD estimate (Kosasih and Brintrup, 2025; Brintrup et al., 2024). The fifth concerns LLM-derived risk signals, which need tests of stability across prompts and model versions and a sample of human-validated extractions before they can feed a credit model (Fang et al., 2026; Jackson et al., 2024). The sixth concerns fair and governed deployment, which calls for studies that measure how coupled scoring changes access to SCF for

firms in regions with weak logistics infrastructure and how interpretable coupling terms affect supervisory acceptance (Fuster et al., 2022; NIST, 2023). Across all six, the field would benefit from shared benchmark data sets that combine logistics and financial records, since the lack of such data is the main reason the two literatures have developed apart (Riahi et al., 2021; Ni et al., 2020).

Managerial and policy implications

For managers, the main implication is organisational. The CFR framework requires the logistics function, the treasury and the credit function to share a common risk model and a common set of scenarios. In many firms these functions report to different executives and use different systems, so the first step is to agree on shared variables, such as the cash conversion cycle and a supplier risk exposure index, that both sides can monitor (Simchi-Levi et al., 2015; Hofmann and Kotzab, 2010). Buyers that run SCF programmes are well placed to lead, because they already see both the physical and financial transactions of their suppliers and have an interest in keeping those suppliers solvent (Tunca and Zhu, 2018). Evidence from industry indicates that AI adoption in operations succeeds when it is tied to specific decisions and supported by data governance, rather than deployed as a general capability (Fosso Wamba et al., 2022; Dubey et al., 2020). Performance dashboards, real-time KPI tracking and accountability frameworks give managers the shared view that coupled risk requires (Ezeako et al., 2024; Tonoyan et al., 2024b; Sakyi et al., 2022), revenue assurance and utility operations analytics show how data-driven monitoring

protects cash flows (Sakyi et al., 2023; Nnabueze et al., 2023), and workforce optimization and enterprise risk models that link HR strategy to operational analytics address the staffing side of resilience (Falemi et al., 2023, 2024).

For lenders and supervisors, the framework suggests that logistics data is a legitimate and possibly powerful input to credit assessment, but that its use carries model risk and fairness obligations that current guidance already covers (Board of Governors of the Federal Reserve System and Office of the Comptroller of the Currency, 2011; Basel Committee on Banking Supervision, 2021). For policy makers concerned with supply chain resilience, it implies that investment in logistics infrastructure and in data standards for trade documents has a financial dividend, since better and more verifiable logistics data lowers the cost of credit for the firms that depend on it (Chod et al., 2020; Belhadi et al., 2022). Studies of AI for resilience after COVID-19 point in the same direction, finding that AI capability improves resilience mainly through visibility and faster response (Modgil et al., 2022; Kraus et al., 2020). Sustainable finance instruments offer a further lever: green bonds and ESG-linked investment can reward operators whose routing and emissions data are verifiable (Sakyi et al., 2024), predictive monitoring of emissions and infrastructure risk supplies the evidence such instruments require (Okojie et al., 2023c), and integrated financial planning in energy distribution shows how operational data can be carried into revenue and investment decisions (Nnabueze et al., 2024). Automated ESG reporting, AI-based ESG auditing, quantitative ESG adoption in SME supply chains and greenhouse gas disclosure obligations define the reporting environment in which such evidence will be used (Okojie et al., 2023b, 2023a; Efobi et al., 2023b; Ominyi and Anichukwueze, 2022).

CONCLUSION

This review examined how artificial intelligence is used to manage financial risk and logistics risk in supply chains and found that the two literatures have grown in parallel rather than together. Credit models for supply chain finance have become accurate but rarely use logistics signals, while disruption, delay and freight forecasting models have become sophisticated but rarely express their outputs as credit or liquidity consequences. Network learning and language models are the two areas where the boundary is beginning to dissolve, since they can place lenders, suppliers, carriers and ports in one graph and can read the early warnings that appear in text before they reach delivery data or financial statements.

The Coupled Flow Risk framework proposed here organises these capabilities into five layers and makes the coupling explicit. Its shared default model lets logistics stress enter credit risk through a single, testable coefficient, and its decision rule weighs expected cost against the joint tail of operational and credit losses, so that combinations of risk that look acceptable on each side separately are recognised

as dangerous together. The framework treats governance as a layer in its own right, because decisions about credit require models that are calibrated, explained, validated and monitored for fairness.

The practical message for firms, lenders and policy makers is that goods and money are one system and should be managed with one risk model. The research message is that the most valuable next studies will estimate the coupling empirically, validate interventions causally, train decision models on joint losses, and establish the data sharing and governance arrangements that make coupled AI both effective and accountable.

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COMPETING INTERESTS

The authors declare no competing interests.

DATA AVAILABILITY

No new data were generated or analysed in this study.

REFERENCES

- [1] Abdulrazaq, K., Yusuf, H. D., Peteranaba, S. F., Osinem, H. E., & Eribenne, F. (2025). A conceptual framework for using Power BI analytics to improve vendor performance management and supply forecasting. *International Journal of Technology, Health and Sustainability*, 1(2), 214-235.
- [2] Abetoh, N. F., & Atakpa, M. I. (2024). Audit analytics in healthcare financial oversight: Leveraging data science to strengthen accountability in multilateral grant ecosystems. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 10(6), 2710-2747. <https://doi.org/10.32628/CSEIT2410791>
- [3] Acemoglu, D., Carvalho, V. M., Ozdaglar, A., & Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, 80(5), 1977-2016. <https://doi.org/10.3982/ECTA9623>
- [4] Adebayo, A., Amadi, C., & Ijagbemi, A. O. (2025). From audit to continuous control: Implementation pathways, governance, and organizational readiness for AI-enabled compliance in critical infrastructure. *International Journal of Computer Science and Mathematical Theory*, 11(8), 88-134. <https://doi.org/10.56201/ijcsmt.vol.11.no8.2025.pg88.134>
- [5] Adelanwa, A., Basnet, A., & Anene, U. N. (2023a). Data driven digital transformation models for lifecycle performance management in infrastructure delivery. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2646-2662. <https://doi.org/10.62225/2583049X.2023.3.6.5968>
- [6] Adelanwa, A., Basnet, A., & Anene, U. N. (2023b). Predictive analytics models for financial risk detection and fraud prevention in public systems. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2663-2679. <https://doi.org/10.62225/2583049X.2023.3.6.5969>
- [7] Adesanya, O. S., Okafor, C. M., Dako, O. F., & Akinola, A. S. (2024). Value-chain automation in beverage logistics: Throughput, capacity, and cost avoidance via queueing models. *International*



- Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 10(4), 1112-1132. <https://doi.org/10.32628/CSEIT251134110>
- [8] Adesuyi, M. O., Akomolafe, O., Olaogun, B. O., Ndukwe, V. U., & Sakyi, J. K. (2023). Global interoperability model for distributed ledger-based cross-border payment systems. *International Journal of Multidisciplinary Research and Growth Evaluation*, 4(6), 1291-1300. <https://doi.org/10.54660/IJMRGE.2023.4.6.1291-1300>
- [9] Adesuyi, M. O., Akomolafe, O., Olaogun, B. O., Ndukwe, V. U., & Sakyi, J. K. (2024). AI-driven risk scoring model for global cross-border trade payment transactions. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(1), 1569-1581. <https://doi.org/10.62225/2583049X.2024.4.1.5281>
- [10] Adesuyi, M. O., Akomolafe, O., Olaogun, B. O., Ndukwe, V. U., & Sakyi, J. K. (2025a). AI-enabled fraud detection ecosystem model for securing international payment channels. *International Journal of Advanced Multidisciplinary Research and Studies*, 5(6), 866-882. <https://doi.org/10.62225/2583049X.2025.5.6.5284>
- [11] Adesuyi, M. O., Akomolafe, O., Olaogun, B. O., Ndukwe, V. U., & Sakyi, J. K. (2025b). Resilience and continuity model for global payment infrastructure under geopolitical risks. *International Journal of Multidisciplinary Research and Growth Evaluation*, 6(4), 1467-1482. <https://doi.org/10.54660/IJMRGE.2025.6.4.1467-1482>
- [12] Agbabiaka, J., Okonkwo, C. S., Ogunwale, O., Mayo, W., & Okeke, O. T. (2019). Supply chain risk management model for EPC and gas processing projects. *Iconic Research and Engineering Journals*, 3(2), 968-980. <https://doi.org/10.64388/IREV3I2-1713124>
- [13] Agboada, P., Ezeako, R., Okoli, I. E., & Ibeh, A. V. (2018). Distributorship and trade finance product design: A conceptual framework for new-to-bank growth in emerging markets. *Iconic Research and Engineering Journals*, 2(5), 552-578. <https://doi.org/10.64388/IREV2I5-1723312>
- [14] Agu, M. U., Akomolafe, O., & Bello, A. (2023a). A comparative review of SOX compliance frameworks in cross-border financial auditing. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2297-2306. <https://doi.org/10.62225/2583049X.2023.3.6.5362>
- [15] Agu, M. U., Akomolafe, O., & Bello, A. (2023b). A review of integrated data management systems for enhancing financial forecasting accuracy. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2335-2344. <https://doi.org/10.62225/2583049X.2023.3.6.5365>
- [16] Agu, M. U., Akomolafe, O., & Bello, A. (2025). Advances in predictive financial risk assessment using Python-based forecasting systems. *International Journal of Computer Science and Mathematical Theory*, 11(11), 131-148. <https://doi.org/10.56201/ijcsmt.vol.11.no11.2025.pg131.148>
- [17] Ahiaek Patrick, M. C., Okonkwo, C. S., Mayo, W., & Okeke, O. T. (2020). A GIS enabled framework for modern ERP procurement processes. *International Journal of Multidisciplinary Research and Growth Evaluation*, 1(5), 499-508. <https://doi.org/10.54660/IJMRGE.2020.1.5.499-508>
- [18] Ahiaek Patrick, M. C., Okonkwo, C. S., Mayo, W., & Okeke, O. T. (2021). Model for data driven vendor evaluation and bid selection using geospatial intelligence. *Shodhshauryam, International Scientific Refereed Research Journal*, 4(4), 426-443. <https://doi.org/10.32628/SHISRRJ214461>
- [19] Aifuwa, S. E., Oshoba, T. O., Ogbuefi, E., Ike, P. N., Nnabueze, S. B., & Olatunde-Thorpe, J. (2020). Predictive analytics models enhancing supply chain demand forecasting accuracy and reducing inventory management inefficiencies. *International Journal of Multidisciplinary Research and Growth Evaluation*, 1(3), 171-181. <https://doi.org/10.54660/IJMRGE.2020.1.3.171-181>
- [20] Akanbi, O., & Sunday, E. A. (2024). An integrated path-planning and slotting optimization model for AMR-enabled high-density warehousing. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(6), 3226-3243. <https://doi.org/10.62225/2583049X.2024.4.6.6181>
- [21] Akin-Oluyomi, O. T., & Akhigbe, R. (2022). A supply chain governance model for enhancing compliance and operational quality across retail networks. *International Journal of Multidisciplinary Research and Growth Evaluation*, 3(6), 860-878. <https://doi.org/10.54660/ijmrge.2022.3.6.860-878>
- [22] Akin-Oluyomi, O. T., & Akhigbe, R. (2023a). A conceptual supply chain leadership model for aligning logistics decisions with enterprise strategy. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(1), 1725-1744. <https://doi.org/10.62225/2583049X.2023.3.1.5340>
- [23] Akin-Oluyomi, O. T., & Akhigbe, R. (2023b). A proposed supply chain analytics framework for improving forecasting accuracy and reducing bottlenecks. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(1), 1686-1703. <https://doi.org/10.62225/2583049X.2023.3.1.5338>
- [24] Akin-Oluyomi, O. T., & Akhigbe, R. (2023c). An advanced framework for improving multi-site operational efficiency using data-driven performance indicators. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(1), 1763-1781. <https://doi.org/10.62225/2583049X.2023.3.1.5343>
- [25] Akin-Oluyomi, O. T., Atima, M. E., & Akinleye, O. K. (2023a). Green procurement strategies for balancing cost efficiency with long-term environmental responsibility. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2183-2193.
- [26] Akin-Oluyomi, O. T., Atima, M. E., & Akinleye, O. K. (2023b). Regulatory compliance and supplier risk assessment frameworks in international pharmaceutical procurement. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2194-2204. <https://doi.org/10.62225/2583049X.2023.3.6.5326>
- [27] Akin-Oluyomi, O. T., Atima, M. E., & Akinleye, O. K. (2024). Cross-border supplier relationship management frameworks for pharmaceutical and global construction sectors. *International Journal of Multidisciplinary Research and Growth Evaluation*, 5(6), 1709-1718. <https://doi.org/10.54660/IJMRGE.2024.5.6.1709-1718>
- [28] Akin-Oluyomi, O. T., Atima, M. E., Akinleye, O. K., & Akokodaripon, D. A. (2020). Using Tableau and Excel for comprehensive profitability analysis in retail procurement operations. *International Journal of Multidisciplinary Research and Growth Evaluation*, 1(5), 385-393. <https://doi.org/10.54660/IJMRGE.2020.1.5.385-393>
- [29] Akin-Oluyomi, O. T., Atima, M. E., Akinleye, O. K., & Okoruwa, P. O. (2023c). Predictive analytics approaches for improving demand forecasting accuracy in e-commerce procurement systems. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2173-2182. <https://doi.org/10.62225/2583049X.2023.3.6.5324>
- [30] Akin-Oluyomi, O. T., Okoruwa, P. O., Babatope, O. M., & Akokodaripon, D. A. (2023d). Evaluating supplier sustainability metrics through data-driven procurement and supply chain frameworks. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2213-2223. <https://doi.org/10.62225/2583049X.2023.3.6.5328>

- [31] Akinlade, O. F., Filani, O. M., & Nwachukwu, P. S. (2024). Automation and digital twins framework reducing procurement errors and turnaround time. *International Journal of Scientific Research in Humanities and Social Sciences*, 1(1), 197-216. <https://doi.org/10.32628/IJSRSSH242564>
- [32] Akinleye, O. K. (2024). A sustainable procurement and resilience framework for post-pandemic pharmaceutical operations. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(1), 1602-1621. <https://doi.org/10.62225/2583049X.2024.4.1.5335>
- [33] Akinleye, O. K., & Adeyoyin, O. (2021). Process automation framework for enhancing procurement efficiency and transparency. *Shodhshauryam, International Scientific Refereed Research Journal*, 4(4), 356-387. <https://doi.org/10.32628/SHISRRJ214458>
- [34] Akinleye, O. K., & Adeyoyin, O. (2022). Supplier relationship management framework for achieving strategic procurement objectives. *Gyanshauryam, International Scientific Refereed Research Journal*, 5(4), 565-598. <https://doi.org/10.32628/GISRRJ225430>
- [35] Akinleye, O. K., Okoruwa, P. O., Babatope, O. M., & Akokodaripon, D. A. (2023). Leveraging big data and business intelligence for optimization of manufacturing sector procurement. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2164-2172. <https://doi.org/10.62225/2583049X.2023.3.6.5323>
- [36] Akokodaripon, D. A., Akinleye, O. K., Okoruwa, P. O., & Babatope, O. M. (2023). Procurement cost optimization strategies: Comparative analyses across UK, Nigeria, and emerging economies. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2224-2234. <https://doi.org/10.62225/2583049X.2023.3.6.5329>
- [37] Akomolafe, O., & Agu, M. U. (2018). A conceptual model for enhancing internal audit quality through technology-enabled risk assessment frameworks. *Iconic Research and Engineering Journals*, 1(9), 458-475.
- [38] Akomolafe, O., & Agu, M. U. (2019). A conceptual framework for developing risk-based internal control models in the insurance and banking sectors. *Iconic Research and Engineering Journals*, 2(8), 335-354. (confirmed on irejournals.com Vol 2 Issue 8 listing; no DOI)
- [39] Akomolafe, O., Agu, M. U., & Bello, A. (2023a). A conceptual model for implementing risk-based auditing in strategic financial management. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2274-2286. <https://doi.org/10.62225/2583049X.2023.3.6.5359>
- [40] Akomolafe, O., Agu, M. U., & Bello, A. (2023b). A quantitative conceptual model for assessing compliance risk in emerging economies. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2287-2296. <https://doi.org/10.62225/2583049X.2023.3.6.5360>
- [41] Akomolafe, O., Agu, M. U., & Bello, A. (2025a). A conceptual model for advancing risk governance through data-driven compliance analytics in financial institutions. *Journal of Accounting and Financial Management*, 11(11), 211-228. <https://doi.org/10.56201/jafm.vol.11.no11.2025.pg211.228>
- [42] Akomolafe, O., Olaogun, B. O., Adesuyi, M. O., Ndukwe, V. U., & Sakyi, J. K. (2022). Smart contract automation model for supplier payment systems and performance benchmarking. *International Journal of Multidisciplinary Research and Growth Evaluation*, 3(6), 827-836. <https://doi.org/10.54660/IJMRGE.2022.3.6.827-836>
- [43] Akomolafe, O., Olaogun, B. O., Adesuyi, M. O., Ndukwe, V. U., & Sakyi, J. K. (2023c). Predictive AI model for remittance liquidity optimization in international payment systems. *International Journal of Multidisciplinary Research and Growth Evaluation*, 4(6), 1301-1311. <https://doi.org/10.54660/IJMRGE.2023.4.6.1301-1311>
- [44] Akomolafe, O., Olaogun, B. O., Adesuyi, M. O., Ndukwe, V. U., & Sakyi, J. K. (2024a). Scalable blockchain payment gateway architecture model for enterprise-grade adoption. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(1), 1552-1568. <https://doi.org/10.62225/2583049X.2024.4.1.5280>
- [45] Akomolafe, O., Olaogun, B. O., Adesuyi, M. O., Ndukwe, V. U., & Sakyi, J. K. (2024b). Smart contract-based dispute resolution model for international supplier. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(1), 1582-1601. <https://doi.org/10.62225/2583049X.2024.4.1.5282>
- [46] Akomolafe, O., Olaogun, B. O., Adesuyi, M. O., Ndukwe, V. U., & Sakyi, J. K. (2025b). Collaborative governance framework for secure cross-border payment data sharing. *International Journal of Advanced Multidisciplinary Research and Studies*, 5(6), 849-865. <https://doi.org/10.62225/2583049X.2025.5.6.5283>
- [47] Akomolafe, O., Olaogun, B. O., Adesuyi, M. O., Ndukwe, V. U., & Sakyi, J. K. (2025c). Global standardization model for next-generation blockchain interoperability in payment systems. *International Journal of Multidisciplinary Research and Growth Evaluation*, 6(6), 820-834. <https://doi.org/10.54660/IJMRGE.2025.6.6.820-834>
- [48] Alieme, J. I., Sule, A., Alieme, Y. A., & Obukadata, V. O. (2023). AI adoption readiness in small and medium-sized enterprises: Barriers, assessment criteria, and a phased implementation framework. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 3127-3157. <https://doi.org/10.62225/2583049X.2023.3.6.6824>
- [49] Aliliele, C., Eboh, E. E., & Oluwo, K. (2024). Advances in variance analytics for cost control in manufacturing and industrial enterprises. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(6), 3163-3185. <https://doi.org/10.62225/2583049X.2024.4.6.6012>
- [50] Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589-609. <https://doi.org/10.1111/j.1540-6261.1968.tb00843.x>
- [51] Aneke, O. B., & Adesemoye, A. C. (2021). Reframing trade and import compliance: A conceptual model for risk-based interdiction of illicit medical products. *International Journal of Scientific Research in Science and Technology*, 8(6), 1226-1248. <https://doi.org/10.32628/IJSRST1229274>
- [52] Aneke, O. B., & Adesemoye, A. C. (2025). Advances in cold chain integrity and good distribution practice for temperature-sensitive pharmaceuticals. *International Journal of Health and Pharmaceutical Research*, 10(3), 99-137. <https://doi.org/10.56201/ijhpr.vol.10.no3.2025.pg99.137>
- [53] Anene, U. N., & Clement, T. (2022). A resilient logistics framework for humanitarian supply chains: Integrating predictive analytics, IoT, and localized distribution to strengthen emergency response systems. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 8(5), 398-424.
- [54] Anene, U. N., & Clement, T. (2024). Localized supply chain solutions for sustainable community development: A strategic model for economic revitalization and regional resilience. *International Journal of Scientific Research in Science and Technology*, 11(5), 736-776. <https://doi.org/10.32628/>



- IJSRST52310378
- [55] Anene, U. N., Obukadata, V. O., Uzundu, C. S., & Ibeh, A. V. (2025). Process optimization in high-volume reverse-logistics operations: A conceptual framework for category-level improvement. *Gulf Journal of Advance Business Research*, 3(12), 1670-1702. <https://doi.org/10.51594/gjabr.v3i12.221>
- [56] Angelopoulos, A. N., & Bates, S. (2023). Conformal prediction: A gentle introduction. *Foundations and Trends in Machine Learning*, 16(4), 494-591. <https://doi.org/10.1561/22000000101>
- [57] Anichukwueze, C. C., Osuji, V. C., & Oguntegbe, E. E. (2021). Blockchain-based architectures for tamper-proof regulatory recordkeeping and real-time audit readiness. *International Journal of Multidisciplinary Research and Growth Evaluation*, 2(6), 485-504. <https://doi.org/10.54660/IJMRGE.2021.2.6.485-504>
- [58] Annan, A. O. (2025). Automated decision-making and anti-discrimination compliance under U.S. law. *International Journal of Advanced Multidisciplinary Research and Studies*, 5(2), 2522-2540. <https://doi.org/10.62225/2583049X.2025.5.2.5784>
- [59] Atakpa, M. I. (2021). A review of predictive analytics models for anti-money laundering detection in commercial banking systems. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 7(2), 778-804. <https://doi.org/10.32628/CSEIT2064813>
- [60] Atakpa, M. I., & Abetoh, N. F. (2022). A systematic review of machine learning advances in financial fraud detection for banking systems. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 8(2), 771-801. <https://doi.org/10.32628/CSEIT23906220>
- [61] Atakpa, M. I., & Abetoh, N. F. (2023). Anomaly detection in financial time-series data: A conceptual model for healthcare and banking applications. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 9(2), 967-997. <https://doi.org/10.32628/CSEIT2342441>
- [62] Awulu, I., Obukadata, V. O., & Williams, I. (2022). Supply chain resilience in the pharmaceutical industry: Strategies for mitigating disruptions and ensuring availability. *International Journal of Management and Organizational Research*, 1(6), 53-71. <https://doi.org/10.54660/IJMOR.2022.1.6.53-71>
- [63] Babatope, O. M., Akokodaripon, D. A., Akinleye, O. K., & Okoruwa, P. O. (2023). The role of data visualization in enhancing strategic procurement decision-making effectiveness. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2205-2212. <https://doi.org/10.62225/2583049X.2023.3.6.5327>
- [64] Ban, G.-Y., & Rudin, C. (2019). The big data newsvendor: Practical insights from machine learning. *Operations Research*, 67(1), 90-108. <https://doi.org/10.1287/opre.2018.1757>
- [65] Barboza, F., Kimura, H., & Altman, E. (2017). Machine learning models and bankruptcy prediction. *Expert Systems with Applications*, 83, 405-417. <https://doi.org/10.1016/j.eswa.2017.04.006>
- [66] Barrot, J.-N., & Sauvagnat, J. (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics*, 131(3), 1543-1592. <https://doi.org/10.1093/qje/qjw018>
- [67] Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: State of the art and future research directions. *International Journal of Production Research*, 57(7), 2179-2202. <https://doi.org/10.1080/00207543.2018.1530476>
- [68] Basel Committee on Banking Supervision. (2021). *Principles for operational resilience*. Bank for International Settlements. <https://www.bis.org/bcbbs/publ/d516.htm>
- [69] Belhadi, A., Kamble, S., Fosso Wamba, S., & Queiroz, M. M. (2022). Building supply-chain resilience: An artificial intelligence-based technique and decision-making framework. *International Journal of Production Research*, 60(14), 4487-4507. <https://doi.org/10.1080/00207543.2021.1950935>
- [70] Bello, A. A., Oduro, D. A., Manu, E. O., Bello, A. D., Leo, A. O., Ukatu, C. E., & Okika, N. (2025a). Enhancing Know Your Customer (KYC) and Anti-Money Laundering (AML) compliance using blockchain: A business analysis approach. *Iconic Research and Engineering Journals*, 8(9), 297-305.
- [71] Bello, A. D., Elebe, O., Hamed, N. I., Okoruwa, P. O., Fadayomi, O., & Omoegun, G. O. (2025b). An advanced regulatory technology framework for improving financial transparency and fraud reporting accuracy. *International Journal of Advanced Multidisciplinary Research and Studies*, 5(6), 1948-1958. <https://doi.org/10.62225/2583049X.2025.5.6.5676>
- [72] Bello, A. D., Elebe, O., Hamed, N. I., Omoegun, G. O., & Fadayomi, O. (2024). A cybersecurity risk management and regulatory compliance framework for financial institutions. *Iconic Research and Engineering Journals*, 8(2), 1180-1193. <https://doi.org/10.64388/IREV8I2-1713553>
- [73] Bello, A., Akomolafe, O., & Agu, M. U. (2023). A conceptual framework for data-driven procurement risk management in multinational enterprises. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2307-2316. <https://doi.org/10.62225/2583049X.2023.3.6.5363>
- [74] Bertsimas, D., & Kallus, N. (2020). From predictive to prescriptive analytics. *Management Science*, 66(3), 1025-1044. <https://doi.org/10.1287/mnsc.2018.3253>
- [75] Birge, J. R. (2015). OM Forum: Operations and finance interactions. *Manufacturing & Service Operations Management*, 17(1), 4-15. <https://doi.org/10.1287/msom.2014.0509>
- [76] Board of Governors of the Federal Reserve System, & Office of the Comptroller of the Currency. (2011). *Supervisory guidance on model risk management* (SR 11-7). <https://www.federalreserve.gov/supervisionreg/srletters/sr1107.htm>
- [77] Bola-Sadipe, D., Aliliele, C., & Eboh, E. E. (2019). Conceptual model for strategic accounting systems strengthening financial transparency and regulatory compliance. *IRE Journals*, 3(6), 535-564. <https://doi.org/10.64388/IREV3I6-1715327>
- [78] Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5-32. <https://doi.org/10.1023/A:1010933404324>
- [79] Brintrup, A., Kosasih, E., Schaffer, P., Zheng, G., Demirel, G., & MacCarthy, B. L. (2024). Digital supply chain surveillance using artificial intelligence: Definitions, opportunities and risks. *International Journal of Production Research*, 62(13), 4674-4695. <https://doi.org/10.1080/00207543.2023.2270719>
- [80] Brintrup, A., Pak, J., Ratiney, D., Pearce, T., Wichmann, P., Woodall, P., & McFarlane, D. (2020). Supply chain data analytics for predicting supplier disruptions: A case study in complex asset manufacturing. *International Journal of Production Research*, 58(11), 3330-3341. <https://doi.org/10.1080/00207543.2019.1685705>
- [81] Bussmann, N., Giudici, P., Marinelli, D., & Papenbrock, J. (2021). Explainable machine learning in credit risk management. *Computational Economics*, 57(1), 203-216. <https://doi.org/10.1007/s10614-020-10042-0>
- [82] Buzacott, J. A., & Zhang, R. Q. (2004). Inventory management with asset-based financing. *Management Science*, 50(9), 1274-1292. <https://doi.org/10.1287/mnsc.1040.0278>

- [83] Caniato, F., Gelsomino, L. M., Perego, A., & Ronchi, S. (2016). Does finance solve the supply chain financing problem? *Supply Chain Management: An International Journal*, 21(5), 534-549. <https://doi.org/10.1108/SCM-11-2015-0436>
- [84] Carbonneau, R., Laframboise, K., & Vahidov, R. (2008). Application of machine learning techniques for supply chain demand forecasting. *European Journal of Operational Research*, 184(3), 1140-1154. <https://doi.org/10.1016/j.ejor.2006.12.004>
- [85] Carvalho, V. M., Nirei, M., Saito, Y. U., & Tahbaz-Salehi, A. (2021). Supply chain disruptions: Evidence from the Great East Japan Earthquake. *The Quarterly Journal of Economics*, 136(2), 1255-1321. <https://doi.org/10.1093/qje/qjaa044>
- [86] Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785-794). <https://doi.org/10.1145/2939672.2939785>
- [87] Chod, J., Trichakis, N., Tsoukalas, G., Aspegren, H., & Weber, M. (2020). On the financing benefits of supply chain transparency and blockchain adoption. *Management Science*, 66(10), 4378-4396. <https://doi.org/10.1287/mnsc.2019.3434>
- [88] Choi, T.-M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management. *Production and Operations Management*, 27(10), 1868-1883. <https://doi.org/10.1111/poms.12838>
- [89] Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *The International Journal of Logistics Management*, 15(2), 1-14. <https://doi.org/10.1108/09574090410700275>
- [90] Cohen, L., & Frazzini, A. (2008). Economic links and predictable returns. *The Journal of Finance*, 63(4), 1977-2011. <https://doi.org/10.1111/j.1540-6261.2008.01379.x>
- [91] Dada, T., Isiekwu, C. P., & Oluwo, K. (2021a). Advances in multinational cash flow consolidation and FX risk control using tiered treasury architecture. *Iconic Research and Engineering Journals*, 4(11), 601-620. <https://doi.org/10.64388/IREV4111-1714351>
- [92] Dada, T., Isiekwu, C. P., & Oluwo, K. (2021b). Designing CRM-based sales forecasting models for multichannel lending institutions. *Iconic Research and Engineering Journals*, 5(3), 451-466. <https://doi.org/10.64388/IREV513-1714352>
- [93] Dolgui, A., & Ivanov, D. (2021). Ripple effect and supply chain disruption management: New trends and research directions. *International Journal of Production Research*, 59(1), 102-109. <https://doi.org/10.1080/00207543.2021.1840148>
- [94] Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics*, 226, 107599. <https://doi.org/10.1016/j.ijpe.2019.107599>
- [95] Eboh, E. E., & Aliliele, C. (2023). Portfolio risk optimization models for venture capital investment strategy and fraud exposure analysis. *Iconic Research and Engineering Journals*, 7(4), 759-792. <https://doi.org/10.64388/IREV714-1715305>
- [96] Eboh, E. E., & Aliliele, C. (2024). AI-driven data analytics framework for risk assessment and detection of venture capital and private equity investment fraud in U.S. capital markets. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 10(6), 2624-2665. <https://doi.org/10.32628/CSEIT2410787>
- [97] Eboh, E. E., & Aliliele, C. (2025a). Advanced financial due diligence models for preventing venture capital investment fraud and strengthening investor protection. *Shodhshauryam, International Scientific Refereed Research Journal*, 8(5), 153-197. <https://doi.org/10.32628/SHISRRJ258526>
- [98] Eboh, E. E., & Aliliele, C. (2025b). Predictive analytics systems for investment risk monitoring in SME FinTech companies and cross-border capital markets. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 11(2), 3969-4010. <https://doi.org/10.32628/CSEIT25113398>
- [99] Eboh, E. E., Aliliele, C., & Odihi, F. (2025). Advances in financial governance and accountability systems in small and medium enterprises. *International Journal of Advanced Multidisciplinary Research and Studies*, 5(6), 2223-2245. <https://doi.org/10.62225/2583049X.2025.5.6.6013>
- [100] Efobi, O. Z., Akinleye, O. K., & Fasawe, O. (2023a). Conceptual framework for developing a resilience index for post-pandemic supply chains. *Shodhshauryam, International Scientific Refereed Research Journal*, 6(2), 421-432.
- [101] Efobi, O. Z., Akinleye, O. K., & Fasawe, O. (2023b). Framework for quantitative evaluation of ESG adoption within SME supply chains in emerging economies. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2317-2334. <https://doi.org/10.62225/2583049X.2023.3.6.5364>
- [102] Ekwunife, D. I., Precious, O. T., Rasul, O. A., Akinlade, O. F., Nwokoro, T. O., & Ikpe, V. I. (2024). Using blockchain technology to maximize supply chain and logistics management in North America. *International Journal of Science and Research Archive*, 12(2), 854-863. <https://doi.org/10.30574/ijrsra.2024.12.2.1096>
- [103] Elebe, O., & Anunagba, C. O. (2025). Responsible artificial intelligence in IT auditing through evidence validation, human oversight, and regulatory compliance. *International Journal of Technology, Health and Sustainability*, 1(2), 310-328.
- [104] Elmachtoub, A. N., & Grigas, P. (2022). Smart "predict, then optimize". *Management Science*, 68(1), 9-26. <https://doi.org/10.1287/mnsc.2020.3922>
- [105] European Parliament and Council of the European Union. (2024). Regulation (EU) 2024/1689 of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). *Official Journal of the European Union*, L, 2024/1689, 12 July 2024. <http://data.europa.eu/eli/reg/2024/1689/oj>
- [106] Eze, F. I., Anene, U. N., & Akinleye, O. K. (2022). Creation of a drug shortage early warning and regulatory response model for essential medicines in global health systems. *Research Journal of Pure Science and Technology*, 5(1), 57-95. <https://doi.org/10.56201/rjpst.v5.no1.2022.pg57.95>
- [107] Eze, F. I., Anene, U. N., & Akinleye, O. K. (2023). Pharmaceutical supply chain governance, environmental risk management, and sustainable access to essential medicines in emerging economies: The PSCG-ERM framework. *International Journal of Health and Pharmaceutical Research*, 8(4), 192-241. <https://doi.org/10.56201/ijhpr.v8.no4.2023.pg192.241>
- [108] Ezeako, R., Ibeh, A. V., Alugwe, S., & Awulu, I. (2024). Performance dashboards and data-driven decision-making in operations management: A conceptual framework for leadership visibility. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(6), 3520-3538. <https://doi.org/10.62225/2583049X.2024.4.6.6930>
- [109] Ezeako, R., Okoli, I. E., Uzundu, C. S., & Ibeh, A. V. (2019). Relationship banking performance: A conceptual framework for portfolio growth and profitability acceleration. *International*



- Journal of Engineering Technology Research & Management*, 3(11), 132-151. <https://doi.org/10.67809/ijetrm.1789907452>
- [110] Fadayomi, O., Bello, A. D., Elebe, O., Hammed, N. I., & Omoegun, G. O. (2024). An adaptive fraud risk scoring model for real-time transaction monitoring at scale. *IJAR International Journal of Banking and Finance Research*, 10(10), 212-230. <https://doi.org/10.56201/ijbfr.v10.no10.2024.pg212.230>
- [111] Fahimnia, B., Tang, C. S., Davarzani, H., & Sarkis, J. (2015). Quantitative models for managing supply chain risks: A review. *European Journal of Operational Research*, 247(1), 1-15. <https://doi.org/10.1016/j.ejor.2015.04.034>
- [112] Falemi, A., Akhigbe, R., & Akin-Oluyomi, O. T. (2023). A supply chain workforce optimization framework for addressing staffing volatility during rapid expansion cycles. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(1), 1745-1762. <https://doi.org/10.62225/2583049X.2023.3.1.5342>
- [113] Falemi, A., Akhigbe, R., & Akin-Oluyomi, O. T. (2024). A conceptual enterprise risk management model that integrates HR strategy with operational analytics. *International Journal of Multidisciplinary Research and Growth Evaluation*, 5(6), 1730-1753. <https://doi.org/10.54660/ijmrge.2024.5.6.1730-1753>
- [114] Fan, S., Wu, Y., & Yang, R. (2025). Measuring firm-level supply chain risk using a generative large language model. *Finance Research Letters*, 77, 107111. <https://doi.org/10.1016/j.frl.2025.107111>
- [115] Fang, J., Su, B., Wang, S., & Wang, B. (2026). Uncovering the risks of digital supply chains: A large language model framework for semantic identification and validation. *International Journal of Production Economics*, 291, 109858. <https://doi.org/10.1016/j.ijpe.2025.109858>
- [116] Filani, O. M., Nnabueze, S. B., Ike, P. N., & Wedraogo, L. (2022). Real-time risk assessment dashboards using machine learning in hospital supply chain management systems. *International Journal of Multidisciplinary Evolutionary Research*, 3(1), 65-76. <https://doi.org/10.54660/IJMER.2022.3.1.65-76>
- [117] Filani, O. M., Nnabueze, S. B., Sakyi, J. K., & Okojie, J. S. (2023). Scenario-based financial modelling for enhancing strategic decision-making and organizational long-term planning. *Journal of Frontiers in Multidisciplinary Research*, 4(2), 251-265. <https://doi.org/10.54660/JFMR.2023.4.2.251-265>
- [118] Fobellah, A. N. (2025a). Cognitive biases in financial decision-making: Implications for audit and risk management in large corporations: A conceptual review. *International Journal of Science and Research Archive*, 16(2), 17-22. <https://doi.org/10.30574/ijrsra.2025.16.2.2273>
- [119] Fobellah, A. N. (2025b). Navigating digital transformation: Auditing artificial intelligence-powered financial systems: A conceptual review. *International Journal of Science and Research Archive*, 16(2), 23-28. <https://doi.org/10.30574/ijrsra.2025.16.2.2274>
- [120] Fobellah, A. N. (2025c). Unintended consequences of financial regulations: A study of corporate compliance burdens: A conceptual review. *International Journal of Science and Research Archive*, 16(2), 29-34. <https://doi.org/10.30574/ijrsra.2025.16.2.2275>
- [121] Fosso Wamba, S., Queiroz, M. M., Guthrie, C., & Braganza, A. (2022). Industry experiences of artificial intelligence (AI): Benefits and challenges in operations and supply chain management. *Production Planning & Control*, 33(16), 1493-1497. <https://doi.org/10.1080/09537287.2021.1882695>
- [122] Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., & Walther, A. (2022). Predictably unequal? The effects of machine learning on credit markets. *The Journal of Finance*, 77(1), 5-47. <https://doi.org/10.1111/jofi.13090>
- [123] Gelsomino, L. M., Mangiaracina, R., Perego, A., & Tumino, A. (2016). Supply chain finance: A literature review. *International Journal of Physical Distribution & Logistics Management*, 46(4), 348-366. <https://doi.org/10.1108/IJPDLM-08-2014-0173>
- [124] Gijsbrechts, J., Boute, R. N., Van Mieghem, J. A., & Zhang, D. (2022). Can deep reinforcement learning improve inventory management? Performance on lost sales, dual-sourcing, and multi-echelon problems. *Manufacturing & Service Operations Management*, 24(3), 1349-1368. <https://doi.org/10.1287/msom.2021.1064>
- [125] Gomm, M. L. (2010). Supply chain finance: Applying finance theory to supply chain management to enhance finance in supply chains. *International Journal of Logistics Research and Applications*, 13(2), 133-142. <https://doi.org/10.1080/13675560903555167>
- [126] Hammed, N. I., Omoegun, G. O., Elebe, O., Fadayomi, O., & Bello, A. D. (2026). An intelligent fraud monitoring model for protecting small and medium enterprises in digital markets. *Iconic Research and Engineering Journals*, 9(7), 1109-1123. <https://doi.org/10.64388/IREV9I7-1713554>
- [127] Heckmann, I., Comes, T., & Nickel, S. (2015). A critical review on supply chain risk: Definition, measure and modeling. *Omega*, 52, 119-132. <https://doi.org/10.1016/j.omega.2014.10.004>
- [128] Hendricks, K. B., & Singhal, V. R. (2003). The effect of supply chain glitches on shareholder wealth. *Journal of Operations Management*, 21(5), 501-522. <https://doi.org/10.1016/j.jom.2003.02.003>
- [129] Hendricks, K. B., & Singhal, V. R. (2005). An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. *Production and Operations Management*, 14(1), 35-52. <https://doi.org/10.1111/j.1937-5956.2005.tb00008.x>
- [130] Ho, W., Zheng, T., Yildiz, H., & Talluri, S. (2015). Supply chain risk management: A literature review. *International Journal of Production Research*, 53(16), 5031-5069. <https://doi.org/10.1080/00207543.2015.1030467>
- [131] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9(8), 1735-1780. <https://doi.org/10.1162/neco.1997.9.8.1735>
- [132] Hofmann, E., & Kotzab, H. (2010). A supply chain-oriented approach of working capital management. *Journal of Business Logistics*, 31(2), 305-330. <https://doi.org/10.1002/j.2158-1592.2010.tb00154.x>
- [133] Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E: Logistics and Transportation Review*, 125, 285-307. <https://doi.org/10.1016/j.tre.2019.03.001>
- [134] Hou, L., Lu, K., & Bi, G. (2024). Predicting the credit risk of small and medium-sized enterprises in supply chain finance using machine learning algorithms. *Managerial and Decision Economics*, 45(4), 2393-2414. <https://doi.org/10.1002/mde.4130>
- [135] Ike, P. N., Aifuwa, S. E., Nnabueze, S. B., Olatunde-Thorpe, J., Ogbuefi, E., Oshoba, T. O., & Akokodaripon, D. A. (2024). Quantitative risk architecture for public-private partnerships: A multi-layered model for allocating public and private risk. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(6), 2669-2682. <https://doi.org/10.62225/2583049X.2024.4.6.5021>

- [136] Ike, P. N., Ogbuefi, E., Nnabueze, S. B., Olatunde-Thorpe, J., Aifuwa, S. E., Oshoba, T. O., & Akokodari, D. (2021). Supplier relationship management strategies fostering innovation, collaboration, and resilience in global supply chain ecosystems. *International Journal of Multidisciplinary Evolutionary Research*, 2(2), 52-62. <https://doi.org/10.54660/IJMER.2021.2.2.52-62>
- [137] Ike, P. N., Ogbuefi, E., Nnabueze, S. B., Olatunde-Thorpe, J., Aifuwa, S. E., Oshoba, T. O., & Akokodari, D. (2022). Lean supply chain practices improving operational efficiency, reducing waste, and enhancing organizational competitiveness globally. *Journal of Frontiers in Multidisciplinary Research*, 3(2), 182-192. <https://doi.org/10.54660/IJFMR.2022.3.2.182-192>
- [138] Ike, P. N., Okojie, J. S., Nnabueze, S. B., Okojoku, Idu, J. O., Filani, O. M., & Ihwughwawwe, S. I. (2025). Digital twin-driven environmental compliance models for sustainable procurement in oil, gas, and utilities. *International Journal of Advanced Multidisciplinary Research and Studies*, 5(5), 562-576. <https://doi.org/10.62225/2583049X.2025.5.5.4960>
- [139] Isiekwu, C. P., Oluwo, K., & Dada, T. (2025). A post-pandemic strategic collaboration model for banks and capital markets: Addressing resilience, recovery, and growth challenges. *International Journal of Advanced Multidisciplinary Research and Studies*, 5(6), 2104-2116. <https://doi.org/10.62225/2583049X.2025.5.6.5877>
- [140] Ivanov, D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. *Transportation Research Part E: Logistics and Transportation Review*, 136, 101922. <https://doi.org/10.1016/j.tre.2020.101922>
- [141] Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. *International Journal of Production Research*, 58(10), 2904-2915. <https://doi.org/10.1080/00207543.2020.1750727>
- [142] Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control*, 32(9), 775-788. <https://doi.org/10.1080/09537287.2020.1768450>
- [143] Jackson, I., Ivanov, D., Dolgui, A., & Namdar, J. (2024). Generative artificial intelligence in supply chain and operations management: A capability-based framework for analysis and implementation. *International Journal of Production Research*, 62(17), 6120-6145. <https://doi.org/10.1080/00207543.2024.2309309>
- [144] Jones, B. C., & Ominyi, M. (2024a). A conceptual framework for harmonizing digital trade regulations in cross-border e-commerce between the United States and Nigeria. *International Journal of Economics and Financial Management*, 9(9), 337-364. <https://doi.org/10.56201/ijefm.v9.no9.2024.pg337.364>
- [145] Jones, B. C., & Ominyi, M. (2024b). Applications of artificial intelligence in customs administration and trade facilitation: A review. *World Journal of Innovation and Modern Technology*, 8(6), 181-217. <https://doi.org/10.56201/wjimt.v8.no6.2024.pg181.217>
- [146] Jones, B. C., & Ominyi, M. (2025). Conceptualizing AI-driven advisory services for expanding trade compliance access to small and medium enterprises. *IIARD International Journal of Economics and Business Management*, 11(12), 441-474. <https://doi.org/10.56201/ijebm.vol.11.no12.2025.pg441.474>
- [147] Jüttner, U. (2005). Supply chain risk management: Understanding the business requirements from a practitioner perspective. *The International Journal of Logistics Management*, 16(1), 120-141. <https://doi.org/10.1108/09574090510617385>
- [148] Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. *Journal of Banking & Finance*, 34(11), 2767-2787. <https://doi.org/10.1016/j.jbankfin.2010.06.001>
- [149] Kleindorfer, P. R., & Saad, G. H. (2005). Managing disruption risks in supply chains. *Production and Operations Management*, 14(1), 53-68. <https://doi.org/10.1111/j.1937-5956.2005.tb00009.x>
- [150] Kosasih, E. E., & Brintrup, A. (2022). A machine learning approach for predicting hidden links in supply chain with graph neural networks. *International Journal of Production Research*, 60(17), 5380-5393. <https://doi.org/10.1080/00207543.2021.1956697>
- [151] Kosasih, E. E., & Brintrup, A. (2025). Towards trustworthy AI for link prediction in supply chain knowledge graph: A neurosymbolic reasoning approach. *International Journal of Production Research*, 63(6), 2268-2290. <https://doi.org/10.1080/00207543.2024.2399713>
- [152] Kouvelis, P., & Zhao, W. (2012). Financing the newsvendor: Supplier vs. bank, and the structure of optimal trade credit contracts. *Operations Research*, 60(3), 566-580. <https://doi.org/10.1287/opre.1120.1040>
- [153] Kraus, M., Feuerriegel, S., & Oztekin, A. (2020). Deep learning in business analytics and operations research: Models, applications and managerial implications. *European Journal of Operational Research*, 281(3), 628-641. <https://doi.org/10.1016/j.ejor.2019.09.018>
- [154] Kumuyi, O., Akeju, B., Uzoka, E., & Ozowara, D. E. (2023). Framework for blockchain-based cross-border data exchange and regulatory transparency. *International Journal of Multidisciplinary Futuristic Development*, 4(1), 99-113. <https://doi.org/10.54660/IJMFD.2023.4.1.99-113>
- [155] Kumuyi, O., Uzoka, E., Akeju, B., & Ozowara, D. E. (2024). Framework for privacy-focused digital identity verification supporting financial inclusion in Africa. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(6), 3150-3162. <https://doi.org/10.62225/2583049X.2024.4.6.6005>
- [156] Lawal, O. A., & Oduleye, T. E. (2018). A review and conceptual framework for tax governance and cross border compliance analytics. *Iconic Research and Engineering Journals*, 2(5), 336-348.
- [157] Lawal, O. A., & Oduleye, T. E. (2019). Conceptualizing data driven executive decision systems for strategic financial planning. *Iconic Research and Engineering Journals*, 3(3), 370-385.
- [158] Lessmann, S., Baesens, B., Seow, H.-V., & Thomas, L. C. (2015). Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. *European Journal of Operational Research*, 247(1), 124-136. <https://doi.org/10.1016/j.ejor.2015.05.030>
- [159] Lim, B., Arik, S. Ö., Loeff, N., & Pfister, T. (2021). Temporal fusion transformers for interpretable multi-horizon time series forecasting. *International Journal of Forecasting*, 37(4), 1748-1764. <https://doi.org/10.1016/j.ijforecast.2021.03.012>
- [160] Liu, Y., Liu, S., & Lu, Y. (2025). Supply chain financial risk assessment: A modified graph attention neural network. *Finance Research Letters*, 86, 108285. <https://doi.org/10.1016/j.frl.2025.108285>
- [161] Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems 30* (pp. 4765-4774). <https://proceedings.neurips.cc/paper/2017/>



- hash/8a20a8621978632d76c43dfd28b67767-Abstract.html
- [162] Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2022). M5 accuracy competition: Results, findings, and conclusions. *International Journal of Forecasting*, 38(4), 1346-1364. <https://doi.org/10.1016/j.ijforecast.2021.11.013>
- [163] Mayo, W., Ogbale, J. I., Okoruwa, P. O., & Babatope, O. M. (2023). Designing an AI-predictive maintenance model for e-commerce systems using machine learning and cloud analytics. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2454-2468. <https://doi.org/10.62225/2583049X.2023.3.6.5418>
- [164] Mbonu, I. S., Aliliele, C., Iwuanyanwu, U., & Uzoka, E. (2021). A conceptual framework for risk based business intelligence architecture in financial technology platforms. *International Journal of Multidisciplinary Research and Growth Evaluation*, 2(6), 731-746. <https://doi.org/10.54660/IJMRGE.2021.2.6.731-746>
- [165] Mbonu, I. S., Aliliele, C., Iwuanyanwu, U., & Uzoka, E. (2022). A conceptual framework for AI enabled IT general controls and SOX audit automation processes. *Gyanshauryam, International Scientific Refereed Research Journal*, 5(5), 384-414. <https://doi.org/10.32628/GISRRJ2256239>
- [166] Mbonu, I. S., Iwuanyanwu, U., Aliliele, C., & Uzoka, E. (2020). A conceptual framework for agile supply chain digital transformation with embedded IT risk and ISO compliance controls. *Iconic Research and Engineering Journals*, 3(11), 566-593. <https://doi.org/10.64388/IREV3111-1714916>
- [167] Medon, J. J., & Oduleye, T. E. (2022). A comprehensive financial reporting model for strengthening compliance and organizational accountability systems. *International Journal of Multidisciplinary Research and Growth Evaluation*, 3(6), 768-777. <https://doi.org/10.54660/IJMRGE.2022.3.6.768-777>
- [168] Medon, J. J., & Oduleye, T. E. (2023). Developing a financial planning model for sustainable profitability in dynamic business environments. *Shodhshauryam, International Scientific Refereed Research Journal*, 6(3), 448-464. <https://doi.org/10.32628/SHISRRJ236926>
- [169] Medon, J. J., & Oduleye, T. E. (2024). An integrated predictive analytics model for enhancing strategic financial forecasting and decision accuracy. *Gyanshauryam, International Scientific Refereed Research Journal*, 7(3), 258-279. <https://doi.org/10.32628/GISRRJ247322>
- [170] Modgil, S., Singh, R. K., & Hannibal, C. (2022). Artificial intelligence for supply chain resilience: Learning from Covid-19. *The International Journal of Logistics Management*, 33(4), 1246-1268. <https://doi.org/10.1108/IJLM-02-2021-0094>
- [171] Moretto, A., Grassi, L., Caniato, F., Giorgino, M., & Ronchi, S. (2019). Supply chain finance: From traditional to supply chain credit rating. *Journal of Purchasing and Supply Management*, 25(2), 197-217. <https://doi.org/10.1016/j.pursup.2018.06.004>
- [172] Mou, W., Wong, W.-K., & McAleer, M. (2018). Financial credit risk evaluation based on core enterprise supply chains. *Sustainability*, 10(10), 3699. <https://doi.org/10.3390/su10103699>
- [173] National Institute of Standards and Technology [NIST]. (2023). *Artificial intelligence risk management framework (AI RMF 1.0)* (NIST AI 100-1). U.S. Department of Commerce. <https://doi.org/10.6028/NIST.AI.100-1>
- [174] Ngonadi, U., Ominyin, M., Anichukwueze, C. C., & Jones, B. C. (2020). Force majeure and contractual resilience in global energy supply chains: A systematic review. *International Journal of Multidisciplinary Research and Growth Evaluation*, 1(5), 1247-1264. <https://doi.org/10.54660/IJMRGE.2020.1.5.1247-1264>
- [175] Ngonadi, U., Ominyin, M., Anichukwueze, C. C., & Jones, B. C. (2022). Real-time compliance pipelines: A review of automated risk monitoring and enterprise data governance. *International Journal of Multidisciplinary Futuristic Development*, 3(2), 66-94. <https://doi.org/10.54660/IJMF.2022.3.2.66-94>
- [176] Ngonadi, U., Ominyin, M., Anichukwueze, C. C., & Jones, B. C. (2023). Advances in standardizing un-standardized compliance controls for high-volume non-traditional distribution networks. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 3178-3201. <https://doi.org/10.62225/2583049X.2023.3.6.6838>
- [177] Ngonadi, U., Ominyin, M., Anichukwueze, C. C., & Jones, B. C. (2025a). Advances in automated governance: Mitigating operational and systemic risks in multi-country delivery networks. *Gulf Journal of Advance Business Research*, 3(12), 1626-1669. <https://doi.org/10.51594/gjabr.v3i12.219>
- [178] Ngonadi, U., Ominyin, M., Uzougbo, N. S., & Jones, B. C. (2025b). Advances in NLP-driven analytics for automated detection of regulatory liabilities in high-volume contracts. *Research Journal of Pure Science and Technology*, 8(8), 142-212. <https://doi.org/10.56201/rjpst.vol.8.no8.2025.pg142.212>
- [179] Nguyen, T., Zhou, L., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. *Computers & Operations Research*, 98, 254-264. <https://doi.org/10.1016/j.cor.2017.07.004>
- [180] Ni, D., Xiao, Z., & Lim, M. K. (2020). A systematic review of the research trends of machine learning in supply chain management. *International Journal of Machine Learning and Cybernetics*, 11(7), 1463-1482. <https://doi.org/10.1007/s13042-019-01050-0>
- [181] Nnabueze, S. B., Ike, P. N., Olatunde-Thorpe, J., Aifuwa, S. E., Oshoba, T. O., Ogbuefi, E., & Akokodaripon, D. (2021). End-to-end visibility frameworks improving transparency, compliance, and traceability across complex global supply chain operations. *International Journal of Multidisciplinary Futuristic Development*, 2(2), 50-60. <https://doi.org/10.54660/IJMF.2021.2.2.50-60>
- [182] Nnabueze, S. B., Sakyi, J. K., Filani, O. M., Okojie, J. S., Abioye, R. F., Okereke, M., & Enow, O. F. (2024). Revenue optimization in energy distribution through integrated financial planning and advanced data-driven frameworks. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(4), 1427-1445. <https://doi.org/10.62225/2583049X.2024.4.4.4937>
- [183] Nnabueze, S. B., Sakyi, J. K., Filani, O. M., Okojie, J. S., Babatope, O. M., & Adanyin, A. (2023). Transforming utility and service operations through automation, data-driven analytics, and customer-centric innovation. *International Journal of Multidisciplinary Evolutionary Research*, 4(2), 40-57. <https://doi.org/10.54660/IJMER.2023.4.2.40-57>
- [184] Notteboom, T., Pallis, T., & Rodrigue, J.-P. (2021). Disruptions and resilience in global container shipping and ports: The COVID-19 pandemic versus the 2008-2009 financial crisis. *Maritime Economics & Logistics*, 23(2), 179-210. <https://doi.org/10.1057/s41278-020-00180-5>
- [185] Nwakamma, S., Ojukwu, J., & Oyesiji, S. O. (2024). LLM-as-a-judge for automated model governance: A review of methods, biases, and release-gating practices. *World Journal of Innovation and Modern Technology*, 8(6), 185-216. <https://doi.org/10.56201/wjimt.v8.no6.2024.pg185.216>
- [186] Nwangwu, C. V., Onwumere, A., & Akano, O. A. (2024). Systems-level throughput optimization: A review of workflow redesign strategies to mitigate logistics bottlenecks. *International Journal*

- of *Multidisciplinary Research and Growth Evaluation*, 5(6), 1969-1980. <https://doi.org/10.54660/IJMRGE.2024.5.6.1969-1980>
- [187] Nwangwu, C. V., Onwumere, A., & Akano, O. A. (2025). Strategic sourcing and spend analytics: A framework for cost reduction and supply shock mitigation. *International Journal of Multidisciplinary Research and Growth Evaluation*, 6(6), 1391-1404. <https://doi.org/10.54660/IJMRGE.2025.6.6.1391-1404>
- [188] Obukadata, V. O., Awulu, I., & Williams, I. (2021). A Lean Six Sigma approach to mitigating pharmacy distribution bottlenecks in developing healthcare settings. *International Journal of Multidisciplinary Research and Growth Evaluation*, 2(6), 1195-1211. <https://doi.org/10.54660/IJMRGE.2021.2.6.1195-1211>
- [189] Obukadata, V. O., Ezeako, R., Okoli, I. E., & Alugwe, S. (2024). AI-enabled synthesis of stakeholder and survey data in operations research: A review of advances and applications. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(6), 3539-3563. <https://doi.org/10.62225/2583049X.2024.4.6.6931>
- [190] Oduleye, T. E., & Medon, J. J. (2021). A data-driven cost management model for improving strategic financial planning and performance evaluation. *International Journal of Multidisciplinary Research and Growth Evaluation*, 2(6), 524-537. <https://doi.org/10.54660/IJMRGE.2021.2.6.524-537>
- [191] Oduleye, T. E., & Medon, J. J. (2023). A quantitative model for measuring the strategic impact of financial analysis on enterprise growth. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(1), 1663-1672. <https://doi.org/10.62225/2583049X.2023.3.1.5334>
- [192] Ogundairo, K. M. (2025). Hardening the autonomous value chain: Lean Six Sigma guardrails and multi-enterprise ETL architecture for agentic supply chain orchestration. *IJAR International Journal of Economics and Business Management*, 11(12), 441-478. <https://doi.org/10.56201/ijebm.vol.11.no12.2025.pg441.478>
- [193] Ogunwale, O., Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2021). Supply chain resilience framework for critical infrastructure and gas processing plants. *Shodhshauryam, International Scientific Refereed Research Journal*, 4(4), 444-461. <https://doi.org/10.32628/SHISRRJ214462>
- [194] Okafor, C. M., Farounbi, B. O., Adesanya, O. S., & Akinola, A. S. (2024). Controls for cross-border payments operations: Correspondent banking risk reduction via end-to-end monitoring. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 10(4), 1050-1071.
- [195] Okojie, J. S., Filani, O. M., Ike, P. N., Okojokwu-Idu, J. O., Nnabueze, S. B., & Ihwughwawwe, S. I. (2023a). Integrating AI with ESG metrics in smart infrastructure auditing for high-impact urban development projects. *International Journal of Multidisciplinary Futuristic Development*, 4(1), 32-44. <https://doi.org/10.54660/IJMF.2023.4.1.32-44>
- [196] Okojie, J. S., Filani, O. M., Ike, P. N., Okojokwu-Idu, J. O., Nnabueze, S. B., Ihwughwawwe, S. I., Enow, O. F., & Abioye, R. F. (2023b). Automated ESG reporting in energy projects using blockchain-driven smart compliance management systems. *International Journal of Multidisciplinary Evolutionary Research*, 4(2), 120-129. <https://doi.org/10.54660/IJMER.2023.4.2.120-129>
- [197] Okojie, J. S., Ike, P. N., Idu, J. O. O., Nnabueze, S. B., Filani, O. M., & Ihwughwawwe, S. I. (2023c). Predictive analytics models for monitoring smart city emissions and infrastructure risk in urban ESG planning. *International Journal of Multidisciplinary Futuristic Development*, 4(1), 45-57. <https://doi.org/10.54660/IJMF.2023.4.1.45-57>
- [198] Okonkwo, C. S., Agbabiaka, J. A., Ogunwale, O., Mayo, W., & Okeke, O. T. (2021a). Conceptual model for materials readiness and maintenance-driven supply chain performance. *International Journal of Multidisciplinary Research and Growth Evaluation*, 2(6), 584-594. <https://doi.org/10.54660/IJMRGE.2021.2.6.584-594>
- [199] Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2024a). Conceptual framework for digital supply chain governance in energy and infrastructure sectors. *Gyanshauryam, International Scientific Refereed Research Journal*, 7(4), 335-356. <https://doi.org/10.32628/GISRRJ247423>
- [200] Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2024b). Framework for secure and scalable supply chain systems supporting national energy reliability. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(6), 2816-2826. <https://doi.org/10.62225/2583049X.2024.4.6.5494>
- [201] Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2024c). Model for predictive procurement planning to sustain operational uptime. *International Journal of Scientific Research in Humanities and Social Sciences*, 1(2), 909-928. <https://doi.org/10.32628/IJSRSSH242772>
- [202] Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2024d). Review of advances in procurement strategy, ERP adoption, and logistics performance. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(6), 2827-2835. <https://doi.org/10.62225/2583049X.2024.4.6.5495>
- [203] Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2024e). Review of digital supply chain models for cost control and operational continuity. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(6), 2836-2846. <https://doi.org/10.62225/2583049X.2024.4.6.5496>
- [204] Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2024f). Supply chain automation framework using service management platforms. *Shodhshauryam, International Scientific Refereed Research Journal*, 7(2), 157-177. <https://doi.org/10.32628/SHISRRJ2472157>
- [205] Okonkwo, C. S., Agbabiaka, J., Okeke, O. T., & Mayo, W. (2025). Framework for national-scale supply chain optimization through integrated IT and procurement systems. *Gulf Journal of Advance Business Research*, 3(12), 1610-1625. <https://doi.org/10.51594/gjabr.v3i12.189>
- [206] Okonkwo, C. S., Ahiaekwe Patrick, M. C., Okeke, O. T., & Mayo, W. (2023a). Framework for integrating IT systems engineering with supply chain operations. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 2580-2589. <https://doi.org/10.62225/2583049X.2023.3.6.5500>
- [207] Okonkwo, C. S., Mayo, W., & Okeke, O. T. (2023b). Conceptual model for asset lifecycle management and inventory visibility. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 10(1), 809-824. <https://doi.org/10.32628/CSEIT2391568>
- [208] Okonkwo, C. S., Ogunwale, O., & Okeke, O. T. (2018a). Framework for strategic procurement optimization in oil and gas operations. *Iconic Research and Engineering Journals*, 1(7), 153-168. <https://doi.org/10.64388/IREV117-1713119>
- [209] Okonkwo, C. S., Ogunwale, O., & Okeke, O. T. (2018b). Model for inventory availability and plant uptime improvement in energy facilities. *Iconic Research and Engineering Journals*, 2(4), 160-172. <https://doi.org/10.64388/IREV214-1713120>



- [210] Okonkwo, C. S., Ogunwole, O., Mayo, W., & Okeke, O. T. (2021b). Framework for regulatory-compliant procurement in high-risk energy environments. *International Journal of Multidisciplinary Research and Growth Evaluation*, 2(6), 595-605. <https://doi.org/10.54660/IJMRGE.2021.2.6.595-605>
- [211] Okonkwo, C. S., Ogunwole, O., Okeke, O. T., & Mayo, W. (2019). Conceptual framework for cost reduction through contract negotiation and vendor governance. *Iconic Research and Engineering Journals*, 2(9), 468-481. <https://doi.org/10.64388/IREV219-1713121>
- [212] Okoruwa, P. O., Babatope, O. M., Akokodari, D. A., & Akinleye, O. K. (2024). Developing integrated digital platforms for enhancing transparency in procurement and supply chain management. *International Journal of Multidisciplinary Research and Growth Evaluation*, 5(6), 1719-1729. <https://doi.org/10.54660/IJMRGE.2024.5.6.1719-1729>
- [213] Okoruwa, P. O., Babatope, O. M., Akokodari, D. A., & Akinleye, O. K. (2025a). Digital procurement transformation approaches for strengthening efficiency in global supply chain management. *International Journal of Multidisciplinary Research and Growth Evaluation*, 6(5), 975-985. <https://doi.org/10.54660/IJMRGE.2025.6.5.975-985>
- [214] Okoruwa, P. O., Fadayomi, O., Bello, A. D., Elebe, O., Hammed, N. I., & Omoegun, G. O. (2025b). An artificial intelligence-driven financial crime investigation framework for analyst decision support. *International Journal of Multidisciplinary Research and Growth Evaluation*, 6(6), 1307-1314. <https://doi.org/10.54660/IJMRGE.2025.6.6.1307-1314>
- [215] Olan, F., Liu, S., Suklan, J., Jayawickrama, U., & Arakpogun, E. O. (2022). The role of artificial intelligence networks in sustainable supply chain finance for food and drink industry. *International Journal of Production Research*, 60(14), 4418-4433. <https://doi.org/10.1080/00207543.2021.1915510>
- [216] Olaogun, B. O., Adesuyi, M. O., Akomolafe, O., Ndukwe, V. U., & Sakyi, J. K. (2023). Regulatory compliance adaptation model for cross-border payment product redesign. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(1), 1651-1662. <https://doi.org/10.62225/2583049X.2023.3.1.5279>
- [217] Olaogun, B. O., Adesuyi, M. O., Akomolafe, O., Ndukwe, V. U., & Sakyi, J. K. (2025). Macroeconomic impact model for blockchain-enabled payment adoption in emerging economies. *International Journal of Multidisciplinary Research and Growth Evaluation*, 6(6), 835-853. <https://doi.org/10.54660/IJMRGE.2025.6.6.835-853>
- [218] Oluwo, K., Bola-Sadipe, D., & Aliliele, C. (2025). Conceptual framework for data analytics driven financial decision making in banking sector organizations. *Shodhshauryam, International Scientific Refereed Research Journal*, 8(5), 259-302. <https://doi.org/10.32628/SHISRRJ258529>
- [219] Oluwo, K., Dada, T., & Isiekwu, C. P. (2024). Transforming insurance underwriting with machine learning: A review and application cases. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(6), 3008-3019. <https://doi.org/10.62225/2583049x.2024.4.6.5876>
- [220] Ominyin, M., & Anichukwueze, C. C. (2021). A systematic review of anti-money laundering and anti-bribery compliance regimes across emerging and developed markets. *International Journal of Economics and Financial Management*, 6(2), 89-118. <https://doi.org/10.56201/ijefm.v6.no2.2021.pg89.118>
- [221] Ominyin, M., & Anichukwueze, C. C. (2022). Reviewing greenhouse gas disclosure and ESG compliance obligations for energy and infrastructure enterprises under evolving regulatory regimes. *International Journal of Economics and Financial Management*, 7(6), 94-124. <https://doi.org/10.56201/ijefm.v7.no6.2022.pg94.124>
- [222] Ominyin, M., & Anichukwueze, C. C. (2023). A review of algorithmic accountability and model risk management approaches in financial services. *Journal of Accounting and Financial Management*, 9(12), 218-238. <https://doi.org/10.56201/jafm.v9.no12.2023.pg218.238>
- [223] Ominyin, M., & Anichukwueze, C. C. (2024). Conceptualizing responsible AI governance structures for automated decision systems in regulated industries. *International Journal of Social Sciences and Management Research*, 10(11), 403-430. <https://doi.org/10.56201/ijssmr.v10.no11.2024.pg.403.430>
- [224] Ominyin, M., Anichukwueze, C. C., & Uzougbo, N. S. (2024). Developing a conceptual framework for AI-assisted compliance monitoring and anomaly detection in high-volume transaction environments. *World Journal of Innovation and Modern Technology*, 8(6), 204-228. <https://doi.org/10.56201/wjimt.v8.no6.2024.pg204.228>
- [225] Ominyin, M., Ngonadi, U., Anichukwueze, C. C., & Jones, B. C. (2021). Shared responsibility and multi-jurisdictional alignment in global supply chain governance. *International Journal of Multidisciplinary Evolutionary Research*, 2(2), 131-147. <https://doi.org/10.54660/IJMER.2021.2.2.131-147>
- [226] Oroojlooyjadid, A., Nazari, M. R., Snyder, L. V., & Takáč, M. (2022). A deep Q-network for the beer game: Deep reinforcement learning for inventory optimization. *Manufacturing & Service Operations Management*, 24(1), 285-304. <https://doi.org/10.1287/msom.2020.0939>
- [227] Ozowara, D. E., Adebayo, A., & Anunagba, C. O. (2025). Advanced conceptual model for strengthening audit quality using data analytics across financial institutions. *International Journal of Advanced Multidisciplinary Research and Studies*, 5(6), 2246-2268. <https://doi.org/10.62225/2583049X.2025.5.6.6050>
- [228] Petersen, M. A., & Rajan, R. G. (1997). Trade credit: Theories and evidence. *The Review of Financial Studies*, 10(3), 661-691. <https://doi.org/10.1093/rfs/10.3.661>
- [229] Pournader, M., Ghaderi, H., Hassanzadegan, A., & Fahimnia, B. (2021). Artificial intelligence applications in supply chain management. *International Journal of Production Economics*, 241, 108250. <https://doi.org/10.1016/j.ijpe.2021.108250>
- [230] Protopappa-Sieke, M., & Seifert, R. W. (2010). Interrelating operational and financial performance measurements in inventory control. *European Journal of Operational Research*, 204(3), 439-448. <https://doi.org/10.1016/j.ejor.2009.11.001>
- [231] Queiroz, M. M., Ivanov, D., Dolgui, A., & Fosso Wamba, S. (2022). Impacts of epidemic outbreaks on supply chains: Mapping a research agenda amid the COVID-19 pandemic through a structured literature review. *Annals of Operations Research*, 319(1), 1159-1196. <https://doi.org/10.1007/s10479-020-03685-7>
- [232] Riahi, Y., Saikouk, T., Gunasekaran, A., & Badraoui, I. (2021). Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions. *Expert Systems with Applications*, 173, 114702. <https://doi.org/10.1016/j.eswa.2021.114702>
- [233] Rockafellar, R. T., & Uryasev, S. (2000). Optimization of conditional value-at-risk. *Journal of Risk*, 2(3), 21-41. <https://doi.org/10.21314/JOR.2000.038>
- [234] Rolf, B., Jackson, I., Müller, M., Lang, S., Reggelin, T., & Ivanov, D. (2023). A review on reinforcement learning algorithms and

- applications in supply chain management. *International Journal of Production Research*, 61(20), 7151-7179. <https://doi.org/10.1080/00207543.2022.2140221>
- [235] Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, 1(5), 206-215. <https://doi.org/10.1038/s42256-019-0048-x>
- [236] Rukh, S., Seyi-Lande, O. B., & Oziri, S. T. (2024). An integrated framework for AI and predictive analytics in supply chain management. *International Journal of Scientific Research in Humanities and Social Sciences*, 1(1), 451-491. <https://doi.org/10.32628/IJSRSSH243671>
- [237] Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2019). Blockchain technology and its relationships to sustainable supply chain management. *International Journal of Production Research*, 57(7), 2117-2135. <https://doi.org/10.1080/00207543.2018.1533261>
- [238] Sakyi, J. K., Eboseremen, B. O., Adebayo, A. O., Essien, I. A., Okojie, J. S., & Soneye, O. M. (2024). Designing a sustainable financing model for emerging economies: Addressing climate goals through green bonds and ESG investments. *International Journal of Multidisciplinary Futuristic Development*, 5(1), 20-33. <https://doi.org/10.54660/IJMF2024.5.1.20-33>
- [239] Sakyi, J. K., Filani, O. M., Nnabueze, S. B., Okojie, J. S., & Ogedengbe, A. O. (2022). Developing KPI frameworks to enhance accountability and performance across large-scale commercial organizations. *Journal of Frontiers in Multidisciplinary Research*, 3(2), 81-93. <https://doi.org/10.54660/IJFMR.2022.3.2.81-93>
- [240] Sakyi, J. K., Nnabueze, S. B., Filani, O. M., & Okojie, J. S. (2023). Revenue assurance strategies leveraging artificial intelligence and big data in service-intensive organizations. *International Journal of Multidisciplinary Evolutionary Research*, 4(2), 58-75. <https://doi.org/10.54660/IJMER.2023.4.2.58-75>
- [241] Salinas, D., Flunkert, V., Gasthaus, J., & Januschowski, T. (2020). DeepAR: Probabilistic forecasting with autoregressive recurrent networks. *International Journal of Forecasting*, 36(3), 1181-1191. <https://doi.org/10.1016/j.ijforecast.2019.07.001>
- [242] Sawik, T. (2011). Selection of supply portfolio under disruption risks. *Omega*, 39(2), 194-208. <https://doi.org/10.1016/j.omega.2010.06.007>
- [243] Shah, R., Oziri, S. T., & Seyi-Lande, O. B. (2025). A framework for leveraging artificial intelligence in strategic business decision-making. *Gulf Journal of Advance Business Research*, 3(11), 1517-1558. <https://doi.org/10.51594/gjabr.v3i11.171>
- [244] Shittu, H., & Nabil, M. (2023). Smart supply chain management with attribute-based encryption access control. In *2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC)* (pp. 198-204). IEEE. <https://doi.org/10.1109/CCWC57344.2023.10099268>
- [245] Simchi-Levi, D., Schmidt, W., Wei, Y., Zhang, P. Y., Combs, K., Ge, Y., Gusikhin, O., Sanders, M., & Zhang, D. (2015). Identifying risks and mitigating disruptions in the automotive supply chain. *Interfaces*, 45(5), 375-390. <https://doi.org/10.1287/inte.2015.0804>
- [246] Sodhi, M. S., Son, B.-G., & Tang, C. S. (2012). Researchers' perspectives on supply chain risk management. *Production and Operations Management*, 21(1), 1-13. <https://doi.org/10.1111/j.1937-5956.2011.01251.x>
- [247] Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, 103(2), 451-488. <https://doi.org/10.1016/j.ijpe.2005.12.006>
- [248] Tonoyan, A., Dada, O., & Ayivi-Donkor, S. S. (2021). Advances in demand forecasting: Machine learning algorithms for revenue projection and financial planning accuracy. *Gyanshauryam, International Scientific Refereed Research Journal*, 4(1), 282-317. <https://doi.org/10.32628/GISRRJ20361>
- [249] Tonoyan, A., Dada, O., & Ayivi-Donkor, S. S. (2022). Conceptual model for predictive cost optimization: Machine learning applications in business transformation analysis. *International Journal of Economics and Business Management*, 8(6), 68-102. <https://doi.org/10.56201/ijebm.v8.no6.2022.pg68.102>
- [250] Tonoyan, A., Dada, O., & Ayivi-Donkor, S. S. (2024a). Advances in supply chain resilience: Predictive models for vendor risk assessment and procurement cost optimization. *International Journal of Social Sciences and Management Research*, 10(11), 525-551. <https://doi.org/10.56201/ijssmr.v10.no11.2024.pg.525.551>
- [251] Tonoyan, A., Dada, O., & Ayivi-Donkor, S. S. (2024b). Real-time KPI tracking systems: A review of automated performance monitoring and data-driven decision making. *World Journal of Innovation and Modern Technology*, 8(6), 247-281. <https://doi.org/10.56201/wjimt.v8.no6.2024.pg247.281>
- [252] Tonoyan, A., Dada, O., & Ayivi-Donkor, S. S. (2025). A conceptual model for real-time route optimization: Algorithmic pathways to delivery profitability and logistics cost reduction. *World Journal of Innovation and Modern Technology*, 9(12), 308-364. <https://doi.org/10.56201/wjimt.v9.no12.2025.pg308.364>
- [253] Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, 122, 502-517. <https://doi.org/10.1016/j.jbusres.2020.09.009>
- [254] Tunca, T. I., & Zhu, W. (2018). Buyer intermediation in supplier finance. *Management Science*, 64(12), 5631-5650. <https://doi.org/10.1287/mnsc.2017.2863>
- [255] Uzougbo, N. S., Ominyi, M., Anichukwueze, C. C., & Jones, B. C. (2024). Advances in algorithmic contract scoring for pre-negotiation yield optimization and risk retention. *International Journal of Computer Science and Mathematical Theory*, 10(6), 169-217. <https://doi.org/10.56201/ijcsmt.v10.no6.2024.pg169.217>
- [256] Walawalkar, G., Adesuyi, M. O., Kalu, A., & Oduleye, T. E. (2025a). Executive financial dashboards for real-time strategic oversight. *International Journal of Advanced Multidisciplinary Research and Studies*, 5(6), 2042-2054. (confirmed from publisher PDF; no DOI shown)
- [257] Walawalkar, G., Kalu, A., Oduleye, T. E., & Adesuyi, M. O. (2025b). Capital efficiency optimization models in high-velocity business environments. *International Journal of Advanced Multidisciplinary Research and Studies*, 5(6), 2029-2041. <https://doi.org/10.62225/2583049X.2025.5.6.5735>
- [258] Walawalkar, G., Oduleye, T. E., Adesuyi, M. O., & Kalu, A. (2026). Next-generation financial analytics frameworks for AI-enabled enterprises. *International Journal of Advanced Multidisciplinary Research and Studies*, 6(1), 1779-1791.
- [259] Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, 176, 98-110. <https://doi.org/10.1016/j.ijpe.2016.03.014>
- [260] Wang, W., He, N., Shao, P., & Zhou, J. (2025). An interpretable multi-model ensemble deep learning framework for forecasting ocean freight indices with external uncertainty factors. *Maritime Economics & Logistics*, 27(4), 628-661. <https://doi.org/10.1057/>



- s41278-025-00321-8
- [261] Wang, Z., Li, Y., Cui, Z., Zheng, W., & Wang, T. (2026). A machine learning-based study of credit risk in supply chain finance of listed service-oriented enterprises in China. *Pacific-Basin Finance Journal*, 96, 103043. <https://doi.org/10.1016/j.pacfin.2025.103043>
- [262] Wedraogo, L., Essandoh, S., Sakyi, J. K., Ibrahim, A. K., Okafor, C. M., Babalola, A. S., & Adenuga, M. A. (2025). Analysis of vendor management practices and their effects on supply chain performance. *International Journal of Multidisciplinary Futuristic Development*, 6(1), 42-54. <https://doi.org/10.54660/IJMF.D.2025.6.1.42-54>
- [263] Wichmann, P., Brintrup, A., Baker, S., Woodall, P., & McFarlane, D. (2020). Extracting supply chain maps from news articles using deep neural networks. *International Journal of Production Research*, 58(17), 5320-5336. <https://doi.org/10.1080/00207543.2020.1720925>
- [264] Wuttke, D. A., Blome, C., & Henke, M. (2013). Focusing the financial flow of supply chains: An empirical investigation of financial supply chain management. *International Journal of Production Economics*, 145(2), 773-789. <https://doi.org/10.1016/j.ijpe.2013.05.031>
- [265] Xu, X., Chen, X., Jia, F., Brown, S., Gong, Y., & Xu, Y. (2018). Supply chain finance: A systematic literature review and bibliometric analysis. *International Journal of Production Economics*, 204, 160-173. <https://doi.org/10.1016/j.ijpe.2018.08.003>
- [266] Zhao, L., & Huchzermeier, A. (2015). Operations-finance interface models: A literature review and framework. *European Journal of Operational Research*, 244(3), 905-917. <https://doi.org/10.1016/j.ejor.2015.02.015>
- [267] Zhu, Y., Xie, C., Wang, G.-J., & Yan, X.-G. (2017). Comparison of individual, ensemble and integrated ensemble machine learning methods to predict China's SME credit risk in supply chain finance. *Neural Computing and Applications*, 28(S1), 41-50. <https://doi.org/10.1007/s00521-016-2304-x>
- [268] Zhu, Y., Zhou, L., Xie, C., Wang, G.-J., & Nguyen, T. V. (2019). Forecasting SMEs' credit risk in supply chain finance with an enhanced hybrid ensemble machine learning approach. *International Journal of Production Economics*, 211, 22-33. <https://doi.org/10.1016/j.ijpe.2019.01.032>