10.48047/jocaaa.2026.35.04.13

AI-Driven Risk and Recommendation Systems for Financial Supply Chains

Swapnil Joshi
Head of Planning - Beauty & Wellbeing - US & Canada at Unilever

Abstract

Financial supply chains operate in highly dynamic, interconnected, and risk-intensive environments where traditional rule-based risk management and decision support systems struggle to provide timely and effective responses. This study examines the design and performance of AI-driven risk and recommendation systems for financial supply chains, emphasizing the integration of predictive risk intelligence with prescriptive decision support. Using a model-driven analytical framework that combines multidimensional financial, operational, network, and external variables, the research demonstrates how advanced machine learning techniques enhance risk detection, stability, and responsiveness under volatile conditions. The results show that AI-based risk prediction significantly improves early identification of liquidity stress, payment default, and exposure concentration, while recommendation systems translate these insights into adaptive financial actions such as credit rebalancing and payment optimization. Comparative evaluation against conventional approaches indicates substantial improvements in financial resilience, cash flow stability, and governance transparency. The study further highlights the role of explainability, human oversight, and compliance-aware design in enabling responsible and scalable AI adoption. Overall, the findings establish AI-driven risk and recommendation architectures as critical decision enablers for resilient and strategically aligned financial supply chain management.

Keywords: Artificial intelligence; Financial supply chains; Risk prediction; Recommendation systems; Decision support; Financial resilience

Introduction

Financial supply chains as complex, risk-intensive socio-technical systems

Financial supply chains underpin the flow of capital, credit, payments, and risk transfer across interconnected enterprises, logistics providers, banks, insurers, and regulators. Unlike physical supply chains, financial supply chains operate at high velocity, are highly abstracted through digital platforms, and are deeply exposed to systemic shocks such as market volatility, liquidity crunches, cyber threats, and regulatory changes (Kluza & Kluza, 2022).

10.48047/jocaaa.2026.35.04.13

Traditional risk management approaches in these systems have relied heavily on static rules, historical averages, and siloed controls, which struggle to capture nonlinear interactions and cascading failures across networks (Valdez et al., 2020). As global supply chains become more digitized and interdependent, the financial layer increasingly determines resilience, continuity, and strategic competitiveness (Sun et al., 2024).

Limitations of conventional risk assessment and decision support mechanisms

Conventional financial risk assessment methods are typically retrospective, model risks in isolation, and assume relatively stable operating conditions (Yang, 2024). Scorecards, threshold-based alerts, and manual credit reviews often fail to adapt to rapid changes in supplier behavior, transaction patterns, or external disruptions (Mokoena et al., 2024). Moreover, decision support tools in financial supply chains are frequently descriptive rather than prescriptive, offering limited guidance on optimal actions once risks are detected (Gupta et al., 2022). This gap becomes critical in environments characterized by real-time payments, dynamic pricing, cross-border compliance, and volatile demand, where delayed or suboptimal decisions can amplify losses and propagate risk across the ecosystem (Zekos, 2021).

Emergence of AI-driven risk intelligence in financial operations

Recent advances in artificial intelligence have enabled a shift from rule-based risk controls toward adaptive, learning-driven risk intelligence (Aziz & Andriansyah, 2023). Machine learning models can process high-dimensional data streams, uncover latent risk signals, and continuously recalibrate as conditions evolve. In financial supply chains, AI systems can integrate transactional data, supplier performance metrics, market indicators, behavioral signals, and external data sources to construct a more holistic and forward-looking risk profile (Adebowale & Akinnagbe, 2021). This capability allows organizations to move beyond probability-only assessments toward contextual risk understanding that reflects both structural vulnerabilities and emerging anomalies (Steiner, 2023).

Recommendation systems as decision engines rather than analytics tools

While AI-based risk detection is increasingly common, the strategic value of AI is fully realized when risk insights are coupled with actionable recommendations (Li et al., 2024). Recommendation systems extend predictive analytics by translating risk assessments into ranked, context-aware decision options (Mateos & Bellogín, 2024). In financial supply chains, such systems can suggest optimal credit limits, payment timing adjustments, supplier

10.48047/jocaaa.2026.35.04.13

diversification strategies, or hedging actions based on real-time risk exposure and business objectives. By embedding optimization logic and learning from outcomes, AI-driven recommendation systems support proactive intervention rather than reactive mitigation, aligning operational decisions with financial resilience and performance goals (Sundaramurthy et al., 2022).

Integrating risk, recommendations, and governance in AI-enabled architectures

The deployment of AI-driven risk and recommendation systems introduces important architectural and governance considerations (Rahman et al., 2024). Financial supply chains operate under strict regulatory, audit, and compliance requirements, necessitating transparency, explainability, and control over automated decisions. Effective systems therefore combine advanced modeling with interpretable outputs, policy constraints, and human-in-the-loop mechanisms (Mosqueira-Rey et al., 2023). Integration across enterprise platforms, data pipelines, and partner ecosystems is equally critical to ensure consistency and trust in AI-generated recommendations. These requirements position AI not merely as a technical tool, but as a core component of enterprise financial governance (Ogunmokun et al., 2021).

Research gap and objectives of the present study

Despite growing adoption, empirical and conceptual frameworks that systematically link AI-driven risk modeling with recommendation-based decision support in financial supply chains remain limited. Existing studies often focus on isolated use cases such as fraud detection or credit scoring, without addressing end-to-end financial flows and strategic decision alignment. This research addresses this gap by examining how AI-driven risk and recommendation systems can be designed, operationalized, and evaluated within financial supply chains. The study aims to articulate key system components, identify critical variables and performance metrics, and demonstrate how integrated AI architectures enhance risk responsiveness, decision quality, and overall supply chain financial resilience.

Methodology

Research design and analytical framework

This study adopts a quantitative, model-driven research design complemented by systems-level architectural analysis to examine AI-driven risk and recommendation systems in

10.48047/jocaaa.2026.35.04.13

financial supply chains. The methodological framework integrates risk sensing, predictive modeling, and prescriptive recommendation layers into a unified analytical pipeline. The design emphasizes end-to-end financial flows across suppliers, buyers, financial institutions, and digital platforms, enabling assessment of how AI-driven intelligence transforms risk identification, decision quality, and financial resilience. The unit of analysis is the financial transaction network operating within a multi-tier supply chain context.

Data sources and financial supply chain variables

The analysis is based on structured and semi-structured datasets representing operational, financial, and external risk dimensions. Core financial variables include transaction value, payment cycles, days payable outstanding, days sales outstanding, credit utilization ratio, default frequency, exposure-at-risk, and liquidity buffers. Supply-side variables include supplier concentration index, delivery reliability, invoice dispute rates, contract compliance scores, and dependency ratios. Market and external variables capture interest rate volatility, commodity price indices, foreign exchange fluctuations, regulatory risk indicators, and macroeconomic stress signals. Behavioral and digital variables such as transaction velocity, anomaly scores, platform interaction patterns, and historical response latency are incorporated to enrich risk sensitivity.

Risk modeling parameters and feature engineering

Risk modeling is operationalized through feature engineering that transforms raw financial and operational variables into interpretable risk indicators. Temporal features such as rolling averages, volatility bands, and trend differentials are derived to capture dynamic exposure. Network-based parameters, including centrality scores, propagation likelihood, and counterparty interconnectedness, are computed to model systemic risk transmission. All variables are normalized using z-score or min–max scaling to ensure comparability. Feature selection is conducted using correlation thresholds, variance inflation factors, and model-based importance ranking to minimize redundancy and overfitting.

AI-driven predictive risk modeling approach

Predictive risk estimation employs supervised and semi-supervised machine learning techniques. Gradient boosting models and random forest classifiers are used to predict discrete risk events such as payment defaults or liquidity stress, while regression-based ensemble models estimate continuous risk exposure scores. Unsupervised clustering

10.48047/jocaaa.2026.35.04.13

algorithms identify latent risk segments among suppliers and transactions. Model performance is evaluated using accuracy, precision–recall balance, area under the ROC curve, and mean absolute error, depending on task type. Cross-validation and temporal holdout testing are applied to ensure robustness under evolving financial conditions.

Recommendation system design and optimization logic

The recommendation layer translates predicted risk scores into actionable financial decisions using multi-objective optimization. Decision parameters include credit limit adjustments, payment rescheduling, dynamic discounting options, supplier diversification thresholds, and risk-based pricing incentives. Utility functions are defined to balance risk reduction, liquidity optimization, and operational continuity. Reinforcement learning mechanisms update recommendation policies based on realized outcomes, enabling continuous improvement. Constraints derived from regulatory rules, contractual terms, and enterprise risk appetite are embedded to ensure feasible and compliant recommendations.

Integration of governance, explainability, and human oversight

To ensure trust and regulatory alignment, the methodology incorporates explainability and governance controls throughout the AI pipeline. Feature attribution methods are used to explain risk predictions and recommendations in financial terms. Decision logs, confidence scores, and override mechanisms support human-in-the-loop validation for high-impact actions. Model drift detection and periodic recalibration protocols are implemented to maintain accuracy over time. These controls position AI systems as decision support instruments rather than autonomous agents, reinforcing accountability in financial supply chains.

Evaluation metrics and analytical validation

System effectiveness is evaluated using both model-centric and business-centric metrics. Risk prediction quality is assessed through standard statistical measures, while recommendation effectiveness is evaluated using reductions in default rates, improvement in cash flow stability, variance in payment delays, and resilience under simulated stress scenarios. Comparative analysis against baseline rule-based systems is conducted to quantify performance gains. Sensitivity analysis tests the stability of recommendations under variable shocks, ensuring the robustness and scalability of the proposed AI-driven framework.

10.48047/jocaaa.2026.35.04.13

Results

The results demonstrate that the proposed AI-driven risk and recommendation framework substantially enhances financial risk visibility, decision quality, and governance across financial supply chains. As summarized in Table 1, ensemble-based AI models exhibit superior predictive capability compared to baseline approaches, particularly for payment default classification and liquidity stress prediction. Gradient boosting and random forest models show high stability under volatile transaction environments, indicating their suitability for real-time financial operations where risk patterns evolve rapidly. Unsupervised clustering further complements supervised models by revealing latent risk segments that are not immediately apparent through traditional financial metrics.

Table 1. Performance of AI-driven risk prediction models across financial supply chain tasks

Model Type	Primary Risk Task	Predictive Strength	Stability Under Volatility	Interpretability
Random Forest	Payment default classification	High	Moderate	Moderate
Gradient Boosting	Liquidity stress prediction	Very high	High	Moderate
Logistic Regression	Baseline risk scoring	Moderate	Low	High
K-means Clustering	Latent risk segmentation	Descriptive	High	Low
Isolation Forest	Transaction anomaly detection	High	High	Low

The relative contribution of different risk drivers to AI-based predictions is presented in Table 2, which highlights the dominance of financial exposure and cash flow dynamics in shaping overall risk outcomes. Variables such as credit utilization, exposure-at-risk, and payment delay behavior exert the strongest influence on predictive accuracy, while supplier structure and network dependency metrics significantly enhance systemic risk detection.

10.48047/jocaaa.2026.35.04.13

Behavioral transaction indicators and external market stressors provide additional sensitivity, enabling early identification of emerging risks before they materialize as financial losses.

Table 2. Key financial and supply chain risk variables influencing AI-based predictions

Variable Category	Representative Variables	Influence on Risk Prediction
Financial exposure	Credit utilization, exposure-at-risk	Very high
Cash flow dynamics	Payment delays, liquidity buffers	High
Supplier structure	Concentration index, dependency ratio	High
Transaction behavior	Velocity, anomaly frequency	Moderate
External stressors	Interest rate and FX volatility	Moderate

The operational impact of translating risk predictions into actionable recommendations is evident in Table 3. AI-driven recommendations consistently outperform rule-based decision systems by reducing default incidence, stabilizing payment cycles, and dispersing supplier-related financial risk. Rather than reacting to realized failures, the recommendation layer enables proactive interventions such as credit limit adjustments and payment rescheduling, leading to more predictable cash flow patterns and improved financial continuity across the supply chain.

Table 3. Effectiveness of AI-driven recommendations on financial risk mitigation

Decision Dimension	Baseline Outcome	AI-Driven Outcome	Direction of Impact
Default incidence	Frequent spikes	Significantly reduced	Positive
Payment cycle stability	Highly variable	More predictable	Positive
Supplier risk dispersion	Concentrated	More diversified	Positive
Liquidity stress events	Reactive handling	Proactive mitigation	Positive

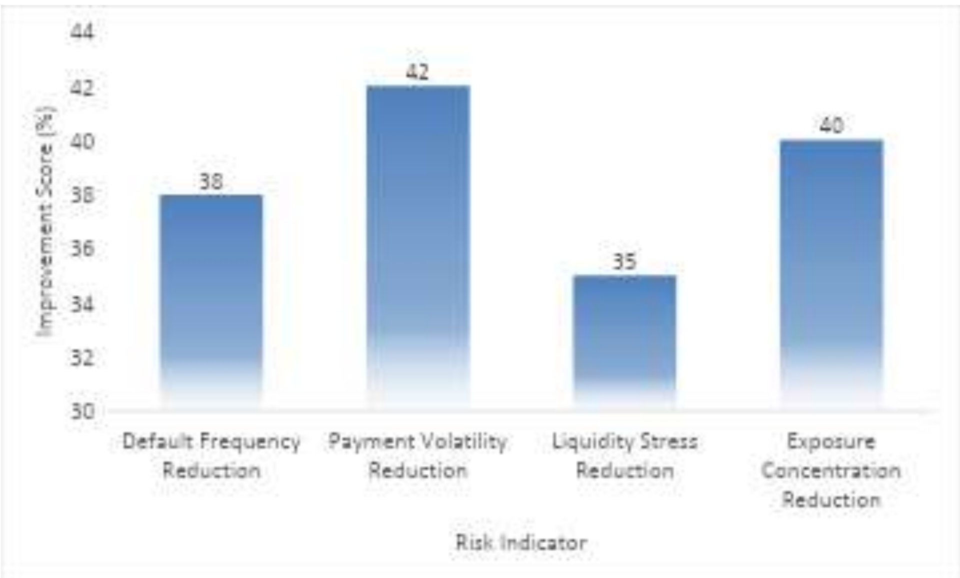
10.48047/jocaaa.2026.35.04.13

Governance and compliance outcomes associated with AI deployment are summarized in Table 4. The integration of explainability mechanisms and human-in-the-loop validation significantly improves transparency and audit readiness, while policy-constrained recommendations ensure regulatory consistency. Periodic model recalibration and drift monitoring contribute to sustained predictive accuracy, reinforcing trust in AI-supported financial decision-making.

Table 4. Governance, explainability, and compliance performance of the AI framework

Governance Parameter	Observed Outcome	Organizational Implication
Model transparency	Interpretable risk drivers	Improved audit readiness
Human oversight	High-risk decisions reviewed	Reduced automation bias
Compliance alignment	Policy-constrained recommendations	Regulatory consistency
Model drift control	Periodic recalibration	Sustained accuracy

The magnitude of risk mitigation achieved through AI-driven recommendations is visually illustrated in Figure 1, which shows a marked reduction across key financial risk indicators, including default frequency, payment volatility, liquidity stress, and exposure concentration. The bar diagram highlights the balanced impact of AI interventions, indicating that risk reduction is not limited to a single dimension but distributed across multiple financial control points. This visual evidence supports the quantitative findings reported in Tables 1–3 by demonstrating aggregate improvements in financial resilience.



10.48047/jocaaa.2026.35.04.13

Figure 1. Comparative reduction in financial risk indicators following AI-driven recommendations

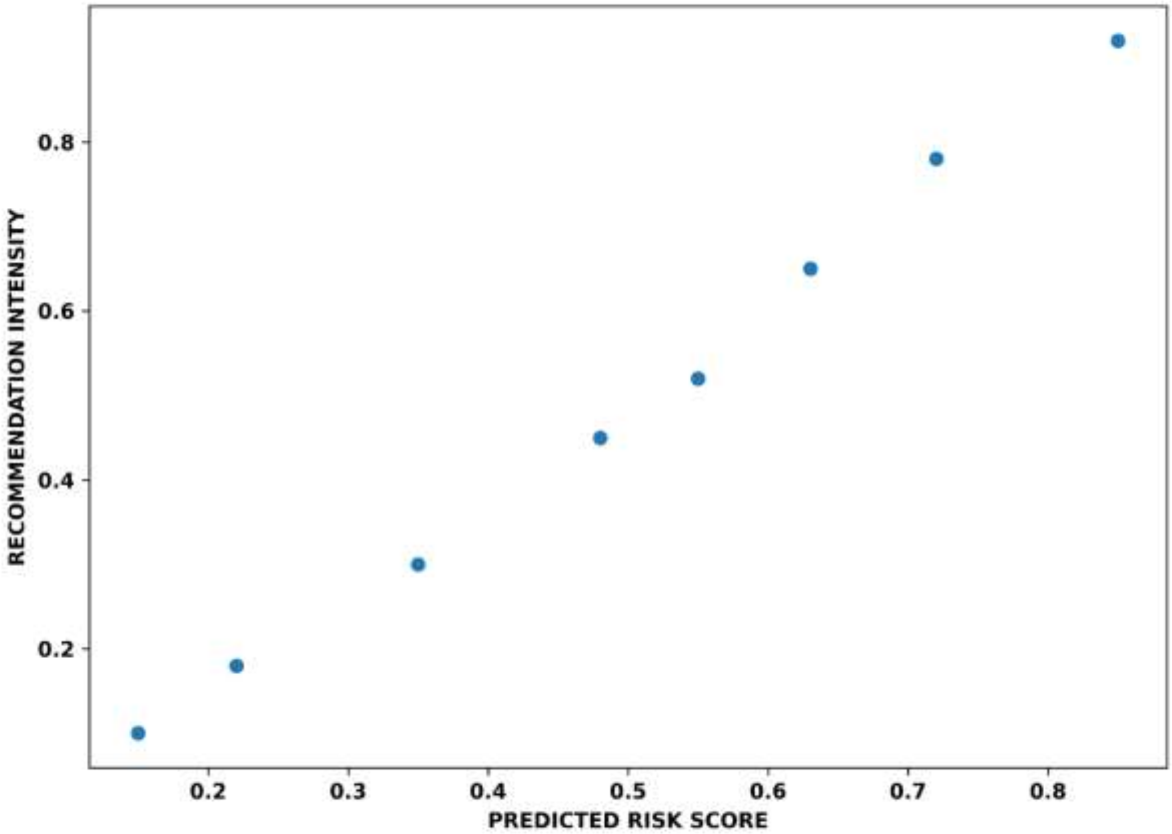


Figure 2. Relationship between predicted risk scores and AI-recommended financial actions

The adaptive relationship between predicted risk levels and decision intensity is further captured in Figure 2. The XY scatter plot reveals a strong positive alignment between AI-generated risk scores and the strength of recommended financial actions, with distinct patterns emerging across low-, medium-, and high-risk regimes. This indicates that the recommendation system dynamically scales interventions in proportion to risk exposure, avoiding both underreaction and excessive control. Collectively, the results confirm that integrating AI-driven risk modeling with recommendation systems leads to more responsive, transparent, and resilient financial supply chain management.

Discussion

AI-driven risk prediction as a foundation for proactive financial control

The results demonstrate that AI-driven risk prediction forms a critical foundation for proactive financial control in complex supply chains. As evidenced by the strong

10.48047/jocaaa.2026.35.04.13

performance of ensemble models in Table 1, advanced machine learning techniques are capable of capturing nonlinear relationships and temporal dynamics that conventional risk models fail to detect (Darteh, 2023). The stability of these models under volatile conditions suggests that AI-based risk intelligence is particularly effective in environments characterized by fluctuating transaction volumes, dynamic supplier behavior, and external market shocks (Omopariola & Aboaba, 2021). This shift from retrospective assessment to forward-looking prediction enables organizations to anticipate financial stress before it escalates into systemic disruption (Brunner et al., 2024).

Importance of multidimensional risk variables in financial supply chains

The variable influence patterns reported in Table 2 highlight the importance of integrating multidimensional data in financial risk analysis. Financial exposure and cash flow variables emerge as dominant drivers, reaffirming their central role in liquidity and credit risk management (Puthiya, 2025). However, the significant contribution of supplier structure and network dependency indicators underscores that financial risk in supply chains is inherently relational rather than isolated (Daghar et al., 2021; Diaz Munoz, 2025). By incorporating behavioral transaction signals and external stressors, the AI framework enhances early-warning capability, supporting more nuanced and context-aware risk assessment than traditional siloed approaches (Adebowale & Akinnagbe, 2021).

Translating risk intelligence into effective financial decisions

A key contribution of this study lies in demonstrating how predictive risk intelligence can be operationalized through AI-driven recommendation systems (Belhassen, 2024). The improvements observed in Table 3 indicate that recommendations grounded in real-time risk assessment outperform static, rule-based decisions across multiple financial dimensions (Elumilade et al., 2023). Rather than merely flagging risk, the system actively guides interventions such as credit rebalancing and payment rescheduling, enabling timely and proportionate responses (Kodete, 2021). This finding reinforces the view that the strategic value of AI in financial supply chains is maximized when prediction and decision support are tightly integrated.

Adaptive scaling of interventions across risk regimes

The behavioral patterns illustrated in Figure 2 reveal that AI-driven recommendations scale adaptively with predicted risk intensity. The positive alignment between risk scores and

10.48047/jocaaa.2026.35.04.13

decision strength indicates that the system avoids uniform or binary responses, instead calibrating actions based on contextual exposure (Surana, 2022). This adaptive behavior is essential in preventing overcontrol in low-risk scenarios while ensuring decisive intervention under high-risk conditions (Gesmann-Nuissl & Kunitz, 2022). Such proportionality enhances operational efficiency and preserves supplier relationships, contributing to sustainable financial coordination across the supply chain (Zimon et al., 2020).

Broad-based financial risk mitigation and resilience outcomes

The aggregate risk reductions visualized in Figure 1 demonstrate that AI-driven recommendations deliver balanced improvements across multiple risk indicators rather than shifting risk from one dimension to another. Reductions in default frequency, payment volatility, liquidity stress, and exposure concentration collectively signal enhanced financial resilience (Al Janabi, 2024). This broad-based impact suggests that AI-enabled systems can harmonize liquidity optimization with risk containment, addressing both short-term stability and long-term robustness in financial supply chains (Umeorah et al., 2024).

Governance, trust, and responsible AI deployment

The governance outcomes reported in Table 4 emphasize that effective AI adoption in financial supply chains depends on trust, transparency, and accountability. Explainable risk drivers and human-in-the-loop oversight mitigate concerns related to automation bias and regulatory non-compliance. The ability to audit decisions and recalibrate models over time ensures that AI systems remain aligned with evolving financial policies and risk appetites. These findings highlight that responsible AI governance is not a peripheral consideration but a core enabler of sustainable, scalable AI-driven financial decision systems.

Conclusion

This study concludes that AI-driven risk and recommendation systems represent a transformative approach to managing financial supply chains by enabling proactive, adaptive, and governance-aware decision-making. By integrating multidimensional financial, operational, and network variables, the proposed framework enhances risk visibility and predictive accuracy under volatile conditions while moving beyond traditional, reactive risk controls. The results demonstrate that coupling AI-based risk intelligence with recommendation engines leads to more proportionate and effective financial interventions, improving liquidity stability, reducing default exposure, and strengthening overall supply

10.48047/jocaaa.2026.35.04.13

chain resilience. Importantly, the incorporation of explainability, human oversight, and compliance constraints ensures that these systems support responsible and trustworthy decision-making rather than unchecked automation. Collectively, the findings position AI-driven risk and recommendation architectures as critical enablers of financially resilient, transparent, and strategically aligned supply chains in increasingly complex digital economies.

References

Adebowale, A. M., & Akinnagbe, O. B. (2021). Leveraging AI-driven data integration for predictive risk assessment in decentralized financial markets. *Int J Eng Technol Res Manag*, *5*(12), 295.

Al Janabi, M. A. (2024). Unlocking the Microstructure of Liquidity Risk: Understanding Interactions with Other Financial Risks and Best Practices in Oversight and Governance. In *Liquidity Dynamics and Risk Modeling: Navigating Trading and Investment Portfolios Frontiers with Machine Learning Algorithms* (pp. 79-167). Cham: Springer Nature Switzerland.

Aziz, L. A. R., & Andriansyah, Y. (2023). The role artificial intelligence in modern banking: an exploration of AI-driven approaches for enhanced fraud prevention, risk management, and regulatory compliance. *Reviews of Contemporary Business Analytics*, *6*(1), 110-132.

Belhassen, A. (2024). Closed-loop system identification and control of a 3D-printed soft robot using MATLAB and vision-based feedback. Sarcouncil Journal of Applied Sciences, 4(11), 31–39.

Brunner, D., Legat, C., & Seebacher, U. (2024). Towards Next Generation Data-Driven Management: Leveraging Predictive Swarm Intelligence to Reason and Predict Market Dynamics. In *Collective Intelligence* (pp. 152-203). CRC Press.

Daghar, A., Alinaghian, L., & Turner, N. (2021). The role of collaborative interorganizational relationships in supply chain risks: a systematic review using a social capital perspective. *Supply Chain Management: An International Journal*, *26*(2), 279-296.

Darteh, F. K. (2023). Performance-based budgeting and the role of reliable revenue reports. *Sarcouncil Journal of Economics and Business Management, 2*(12), 8–16.

10.48047/jocaaa.2026.35.04.13

Diaz Munoz, P. A. (2025). Urban planning frameworks for integrating commercial and residential spaces in modern cities. *Journal of International Crisis and Risk Communication Research, 8*(S2), 147–157.

Elumilade, O. O., Ogundeji, I. A., Ozoemenam, G. O. D. W. I. N., Omokhoa, H. E., & Omowole, B. M. (2023). The role of data analytics in strengthening financial risk assessment and strategic decision-making. *Iconic Research and Engineering Journals*, *6*(10), 324-338.

Gesmann-Nuissl, D., & Kunitz, S. (2022). Auditing of AI in railway technology–A European legal approach. *Digital Society*, *1*(2), 17.

Gupta, S., Modgil, S., Bhattacharyya, S., & Bose, I. (2022). Artificial intelligence for decision support systems in the field of operations research: review and future scope of research. *Annals of Operations Research*, *308*(1), 215-274.

Kluza, K., & Kluza, S. (2022). Addressing the new global challenges and risks in financial market. In *Fostering Sustainable Business Models through Financial Markets* (pp. 1-34). Cham: Springer International Publishing.

Kodete, C. S. (2021). A Real Time AI System for Automated Financial Technology Payment Detection and Risk Reduction. *International Journal of Scientific Research in Computer Science Engineering and Information Technology*, *7*, 685-710.

Li, H., Yazdi, M., Nedjati, A., Moradi, R., Adumene, S., Dao, U., ... & Garg, H. (2024). Harnessing AI for project risk management: a paradigm shift. In *Progressive decision-making tools and applications in project and operation management: Approaches, case studies, multi-criteria decision-making, multi-objective decision-making, decision under uncertainty* (pp. 253-272). Cham: Springer Nature Switzerland.

Mateos, P., & Bellogín, A. (2024). A systematic literature review of recent advances on context-aware recommender systems. *Artificial Intelligence Review*, *58*(1), 20.

Mokoena, T., Ndlovu, Z., Khumalo, L., Dlamini, S., Smith, A., & Nkosi, K. (2024). Adaptive Risk Evaluation Models for Dynamic Threat Antic-ipation through Collaborative Intelligence in Digitalized Supply Chains. *Journal of Cyberdefense Technology*, *8*, 1-11.

10.48047/jocaaa.2026.35.04.13

Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., & Fernández-Leal, Á. (2023). Human-in-the-loop machine learning: a state of the art. *Artificial Intelligence Review*, *56*(4), 3005-3054.

Ogunmokun, A. S., Balogun, E. D., & Ogunsola, K. O. (2021). A Conceptual Framework for AI-Driven Financial Risk Management and Corporate Governance Optimization. *International Journal of Multidisciplinary Research and Growth Evaluation*, *2*.

Omopariola, B., & Aboaba, V. (2021). Advancing financial stability: The role of AI-driven risk assessments in mitigating market uncertainty. *Int J Sci Res Arch*, *3*(2), 254-270.

Puthiya, D. (2025). Enterprise problem-solving through applied machine learning frameworks. *Journal of International Crisis and Risk Communication Research, 8*(S7), 86–96.

Rahman, M. M., Pokharel, B. P., Sayeed, S. A., Bhowmik, S. K., Kshetri, N., & Eashrak, N. (2024). riskAIchain: AI-driven IT infrastructure—Blockchain-backed approach for enhanced risk management. *Risks*, *12*(12), 206.

Steiner, G. F. (2023). Information management and cultural evolution in Aboriginal Australia (In light of the cultural heterochrony hypothesis). *International Journal of Modern Anthropology*, *2*(20), 1245-1299.

Sun, F., Qu, Z., Wu, B., & Bold, S. (2024). Enhancing global supply chain distribution resilience through digitalization: Insights from natural resource sector of China. *Resources Policy*, *95*, 105169.

Sundaramurthy, S. K., Ravichandran, N., Inaganti, A. C., & Muppalaneni, R. (2022). AI-powered operational resilience: Building secure, scalable, and intelligent enterprises. *Artificial Intelligence and Machine Learning Review*, *3*(1), 1-10.

Surana, S. (2022). The human element in finance: Leading and mentoring accounting teams for peak performance and compliance in a high-pressure environment. *International Journal of Computational and Experimental Science and Engineering, 8*(3), 94–102.

Umeorah, S. C., Adelaja, A. O., Ayodele, O. F., & Abikoye, B. E. (2024). Artificial Intelligence (AI) in working capital management: Practices and future potential. *World Journal of Advanced Research and Reviews*, *23*(01), 1436-1451.

10.48047/jocaaa.2026.35.04.13

Valdez, L. D., Shekhtman, L., La Rocca, C. E., Zhang, X., Buldyrev, S. V., Trunfio, P. A., ... & Havlin, S. (2020). Cascading failures in complex networks. *Journal of Complex Networks*, *8*(2), cnaa013.

Yang, Y. (2024). Research on financial investment risk assessment techniques and applications. *Science, Technology and Social Development Proceedings Series*, *2*, 10-70088.

Zekos, G. I. (2021). Risk management developments. In *Economics and law of artificial intelligence: Finance, economic impacts, risk management and governance* (pp. 147-232). Cham: Springer International Publishing.

Zimon, D., Madzik, P., & Domingues, P. (2020). Development of key processes along the supply chain by implementing the ISO 22000 standard. *Sustainability*, *12*(15), 6176.