Ndejje University Journal Of Interdisciplinary Studies,
Volume 2, Issue 2 (September 2026)
eISSN:3079-7683 DOI:

The role of supply chain intelligence on risk mitigation in manufacturing firms in Uganda

[1]Christine Nabanoba, Department of Management and Economics, Ndejje University, Uganda, cnabanoba@ndejjeuniversity.ac.ug, ORCID: 0009-0003-4132-9953
[2]Geoffrey Ssebabi Mutumba, Department of Management and Economics, Ndejje University, Uganda gmutumba@ndejjeuniversity.ac.ug, ORCID: 0000-0001-9535-7659

How to cite this article:
Mutumba, S, G., & Nabanoba, C. (2026). The role of supply chain intelligence on risk mitigation in manufacturing firms in Uganda. Ndejje University Journal of Interdisciplinary, Vol 2 (2), DOI:

Abstract

Manufacturing firms in Uganda operate within supply chains characterised by high baseline risk exposure, driven by infrastructural deficits, institutional volatility, and limited access to formal risk-management instruments. This narrative review examines the role of supply chain intelligence (SCI) — defined as the systematic acquisition, integration, analysis, and dissemination of supply chain data for risk-oriented decision support — in strengthening risk mitigation capabilities within Uganda's manufacturing sector. The review is organised around a three-dimensional analytical framework encompassing risk visibility, decision agility, and contextual fit. Drawing on a synthesis of the global SCI literature and the limited but growing body of empirical work from Uganda, the review assesses the conceptual foundations and enabling technologies of SCI, catalogues the risk typologies prevalent in Ugandan manufacturing, evaluates the mechanisms through which SCI translates into risk mitigation outcomes, and analyses the barriers and enablers shaping SCI adoption in developing-country contexts. The evidence indicates that while SCI offers genuine potential for improving risk outcomes, its effectiveness is contingent on alignment with Uganda's institutional and infrastructural realities. The review identifies a critical gap between the volume of developed-economy SCI research and the near-absence of primary empirical studies grounded in Ugandan manufacturing, and calls for context-specific research that tests SCI interventions under the conditions that characterise Uganda's supply chain environment.

Keywords: ***Supply chain intelligence, risk mitigation, manufacturing, Uganda, developing economies, supply chain risk management, predictive analytics***

Introduction and Background

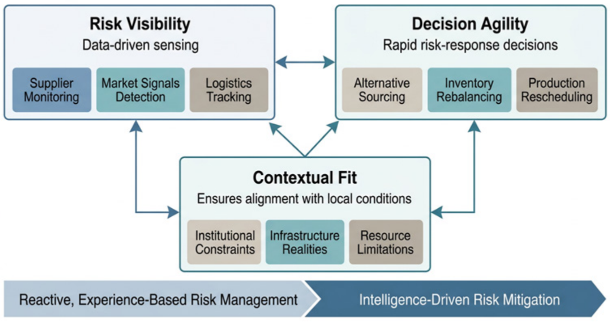
Manufacturing firms in Uganda face supply chain risk that is both structurally distinct from and more severe than that experienced by manufacturers in developed economies. The country's manufacturing sector, which contributed approximately 8.3% to GDP and operates within supply chains characterised by unreliable transport infrastructure, intermittent energy supply, high import dependency for raw materials, and limited access to formal credit and insurance mechanisms (Olwor, 2023). These structural conditions amplify the impact of disruptions that would be manageable in more developed industrial ecosystems: a supplier delay becomes a production shutdown, a currency fluctuation becomes a liquidity crisis, and a seasonal flood becomes a protracted supply discontinuity.

The global supply chain management literature has undergone a rapid expansion of research on supply chain intelligence (SCI) the systematic use of data acquisition, integration, analytics, and dissemination technologies to generate actionable insights for supply chain decision-making (Yang et al., 2021). The proliferation of Internet of Things (IoT) sensors, cloud-based big data platforms, and machine learning algorithms has created a technological toolkit capable of detecting emerging supply chain risks, predicting disruption trajectories, and recommending optimal mitigation responses (Brintrup et al., 2019; Ivanov & Dolgui, 2020). Yet the application of these tools has been overwhelmingly concentrated in developed-economy manufacturing contexts, where reliable digital infrastructure, abundant data streams, and skilled analytical workforces are available (Dou et al., 2024).

This review addresses the intersection of these two observations. It examines the role of supply chain intelligence in risk mitigation within Uganda's manufacturing firms, evaluating both the potential of SCI to improve risk outcomes and the constraints that shape its practical adoption. The review is organised around a three-dimensional analytical framework:

1. Risk visibility is the capacity of SCI to detect, monitor, and characterise supply chain threats through data-driven sensing, moving firms from reactive to anticipatory risk awareness;
2. Decision agility is the speed and quality of risk-mitigation responses enabled by intelligence, measured by the reduction in the detection-to-response gap; and
3. Contextual fit is the degree to which SCI tools and practices align with the institutional, infrastructural, and resource constraints of Uganda's manufacturing sector.

Figure 1. Analytical framework for SCI-driven risk mitigation



This framework, illustrated in Figure 1, positions SCI as a structured intervention against the baseline of reactive, experience-based risk management that still dominates among Ugandan manufacturers. The framework also serves as an evaluative lens: it asks not simply whether SCI "works" but under what conditions, for which types of risk, and with what degree of adaptation to local context.

The importance of this paper in procurement management literature is to synthesise and systematically profile the previous studies in such a way that allows easy comprehension of supply chain risks. The review identifies four priorities for future research. First, longitudinal studies that track SCI adoption and risk outcomes in Ugandan manufacturing firms over time are needed to establish whether the relationship between SCI and risk mitigation observed in developed-economy contexts holds under Uganda's conditions. Second, comparative analyses across East African manufacturing sectors examining how SCI adoption and effectiveness vary across different industry structures, firm sizes, and supply chain configurations and how this would substantially strengthen the evidence base for context-specific recommendations. Third, the development of context-appropriate SCI maturity models that account for the infrastructural, institutional, and organisational specificities of developing-country manufacturing would provide practical guidance for firms navigating the adoption decision. Fourth, intervention studies that test specific SCI tools such as mobile-based supplier monitoring, predictive analytics for currency risk, IoT-enabled cold chain management in Ugandan manufacturing settings would provide the direct causal evidence that is currently absent from the literature.
Finally in the novelty of this study is in the Analytical Spectrum that analyses the Descriptive to Prescriptive Intelligence as in empirical studies. The analytical capability of SCI can be organised along a maturity spectrum progressing through four layers: descriptive, diagnostic, predictive, and prescriptive intelligence. This spectrum, synthesised from the frameworks advanced by (Jeyasheeli et al., 2026; Tiwari et al., 2018; Yang et al., 2021), represents a progressive capability ladder in which each layer builds on the data quality and analytical maturity of preceding layers.

The question of whether SCI can strengthen risk mitigation in Ugandan manufacturing is not a question about technology alone. It is a question about the interaction between technology and context about whether intelligence tools that were designed for data-rich, infrastructure-rich environments can be adapted to serve firms operating under fundamentally different conditions. The answer, as this review suggests, is that they can, but only if the adaptation is taken seriously: not as an afterthought in the implementation process but as the central design principle from the outset.

Road map

The review is structured as follows. Section 2 establishes the conceptual literature on the foundations of SCI, delineating its scope, components, enabling technologies, and analytical maturity spectrum. Section 3 develops a methodology on taxonomy of supply chain risks specific to Ugandan manufacturing, categorising them across operational, infrastructural, and environmental-institutional layers and examines the evidence on how SCI capabilities translate into risk mitigation outcomes through the pathways of early warning, decision agility, and organisational learning. Finally it concludes with a synthesis of findings and directions for future research.

Literature on Conceptual Foundations of Supply Chain Intelligence

This section establishes the conceptual and technological foundations of supply chain intelligence, distinguishing it from related constructs and mapping its analytical maturity spectrum. The discussion proceeds from definitional clarity to technological infrastructure to analytical capability, providing the conceptual toolkit needed to evaluate SCI's role in the Ugandan manufacturing context examined in subsequent sections.

Supply chain intelligence occupies a conceptual space that overlaps with, yet is distinct from, several related constructs in the supply chain management literature. Supply chain visibility refers to the capacity to track materials, products, and information flows across the supply chain and is primarily concerned with transparency and traceability (Dubey et al., 2017). Business intelligence encompasses the broader organisational infrastructure for data-driven decision-making, including reporting, dashboards, and descriptive analytics, but lacks the supply chain-specific risk orientation that defines SCI. Supply chain analytics, as described by (Tiwari et al., 2018), applies quantitative methods to supply chain data but does not necessarily integrate the external environmental scanning and multi-source data fusion that characterise intelligence functions.

SCI, by contrast, is distinguished by three defining features. First, it is risk-oriented: its primary purpose is to identify, assess, and support responses to supply chain threats rather than to optimise routine operational performance (Yang et al., 2021). Second, it is forward-looking: it emphasises predictive and prescriptive analytics that project future states and recommend actions, rather than merely describing past performance (Dou et al., 2024). Third, it is integrative: it combines internal operational data with external data sources including market intelligence, weather forecasts, geopolitical indicators, and supplier financial health signals to create a multi-dimensional risk picture (Brintrup et al., 2019).

The core components of SCI can be organised into four functional layers. Data acquisition encompasses the sensing infrastructure such as IoT devices, enterprise systems, and external data feeds that captures supply chain signals. Data integration involves the aggregation, cleaning, and harmonisation of heterogeneous data streams into a unified analytical platform. Data analysis applies statistical and machine learning methods to detect patterns, anomalies, and risk signals. Dissemination delivers intelligence outputs to decision-makers through dashboards, alerts, and decision-support interfaces.

In the context of developing-economy supply chains, the boundary conditions of SCI require careful specification. While the four-layer model is conceptually universal, its practical instantiation in Uganda is constrained by data sparsity, infrastructure unreliability, and the prevalence of informal supply chain relationships that resist digitisation. These constraints do not invalidate the SCI framework but demand that its application be evaluated against the contextual-fit dimension introduced in Section 1.

The technological infrastructure underpinning modern SCI rests on three interconnected pillars: Internet of Things (IoT) devices for real-time data capture, cloud-based big data platforms for storage and aggregation, and machine learning algorithms for predictive and prescriptive analytics. (Golan et al., 2020) provide a systematic review of resilience analytics across supply chain modelling, documenting the convergence of these technologies toward integrated digital platforms capable of end-to-end supply chain visibility and risk assessment. IoT devices including RFID tags, GPS trackers, and environmental sensors enable the continuous monitoring of material flows, storage conditions, and transport status. In developed-economy manufacturing, IoT deployments have reached sufficient maturity to support real-time supply chain control towers that aggregate sensor data across multiple tiers of the supply network (Schäfer et al., 2022). The application of blockchain technology to IoT data streams has further enabled tamper-proof provenance tracking and automated smart-contract responses to supply chain disruptions (Durán et al., 2024). Big data platforms provide the storage and computational infrastructure needed to process the volume, velocity, and variety of data generated by IoT-enabled supply chains. The integration of structured operational data with unstructured external data — including social media sentiment, news feeds, and satellite imagery represents a significant frontier in SCI capability, enabling the detection of weak signals that precede supply chain disruptions (Jeyasheeli et al., 2026). Predictive analytics, powered by machine learning and deep learning algorithms, transforms raw data into forward-looking risk signals. (Brintrup et al., 2019) demonstrate the application of predictive machine learning to supplier disruption forecasting in complex asset manufacturing, showing that data-driven models can identify at-risk suppliers with accuracy substantially exceeding rule-based approaches. Digital twin technology, as conceptualised by (Ivanov & Dolgui, 2020), extends predictive analytics to the simulation of disruption scenarios and the evaluation of alternative mitigation strategies in a risk-free virtual environment. (Hossain et al., 2024) further establish that digital twin technologies, when combined with supply chain disruption mitigation strategies, significantly enhance supply chain resilience, with strategic fit moderating the strength of this relationship. However, the gap between technology availability in developed economies and adoption feasibility in Uganda is substantial. The IoT infrastructure that underpins real-time SCI in developed contexts reliable power supply, ubiquitous internet connectivity, and affordable sensor hardware cannot be assumed in Uganda's manufacturing environment. The implications of this gap are examined in depth, where the barriers to SCI adoption are analysed.

Descriptive intelligence answers the question "what happened?" It aggregates historical supply chain data to characterise past performance including delivery reliability, supplier defect rates, inventory turnover, and disruption frequency. Descriptive analytics is the most widely deployed layer in both developed and developing-economy supply chains because it requires only basic data collection and reporting infrastructure. For Ugandan manufacturers, descriptive intelligence represents the most accessible entry point to SCI, as it can be supported by relatively simple tools such as spreadsheet-based tracking and basic enterprise resource planning (ERP) modules. Diagnostic intelligence addresses "why did it happen?" by identifying root causes of observed supply chain outcomes. It employs techniques such as correlation analysis, root-cause analysis, and statistical process control to link disruptions to their underlying drivers. Diagnostic capability requires higher data granularity and analytical sophistication than descriptive intelligence, as it depends on the ability to trace outcomes across multiple supply chain tiers and time periods.

Predictive intelligence projects "what will happen?" by applying machine learning and statistical forecasting to historical and real-time data. It is the layer at which SCI transitions from retrospective to forward-looking risk management. (Dou et al., 2024) demonstrate that predictive models incorporating production cost, disruption cost, and reliability parameters can identify high-risk supply chain nodes before disruptions materialise. The predictive layer is the most researched in the current SCI literature, reflecting the growing availability of machine learning tools and the clear value proposition of early warning capability.

Prescriptive intelligence recommends "what should be done?" by combining predictive models with optimisation algorithms to generate actionable risk-response strategies. It represents the highest maturity level of SCI and remains the least developed in practice, even in advanced manufacturing contexts. The prescriptive layer requires not only accurate predictive models but also decision-support systems that can evaluate trade-offs across multiple objectives including cost, service level, and risk exposure under uncertainty.

Table 1. Analytical layers of supply chain intelligence

Layer	Core question	Key techniques	Adoption in developing economies
Descriptive	What happened?	Data aggregation, dashboards, reporting	Most common; accessible with basic tools
Diagnostic	Why did it happen?	Correlation analysis, root-cause analysis	Limited; requires multi-tier data traceability
Predictive	What will happen?	Machine learning, statistical forecasting	Rare; dependent on data volume and quality
Prescriptive	What should be done?	Optimisation, decision-support systems	Very rare; requires mature analytical infrastructure

Table 1 maps the four analytical layers against their core questions, key techniques, and current adoption levels in developing-economy contexts. The progression from descriptive to prescriptive intelligence represents not merely a technological upgrade but a fundamental shift in the risk management paradigm from reactive to anticipatory, and from experience-based to data-driven decision-making. For Ugandan manufacturers, the practical question is not whether the prescriptive layer is achievable in the short term but where on the spectrum the greatest marginal gains in risk mitigation can be realised given existing resource constraints.

Literature search and compilation

The search protocol involved using digital search engine to find related studies. The search used these key words "role of supply chain intelligence risk mitigation in manufacturing firms." The summary results are shown in table 2.

TABLE 2: literature review table summarizing related articles on the role of supply chain intelligence risk mitigation in manufacturing firms in Uganda.

S.NO	SOURCE	THEORIES	VARIABLES	METHODS	FINDINGS
1	Amir Hossein Ordibazar e'tal (2024)	nformation Processing Theory & Social technical Systems theory	SCRM; Identification, Assessment, Mitigation and Monitoring.	1.Qualitative approach 2.PRISMA	1.Multi-echelon approach that accounts for both internal and external factors 2. Little attention is paid on external events 3. Little attention has been paid to improving the output's explainability. 4. Applying AI methods in SCRM needs to be studied further.
2	Samir Ali Syed (2025)	Digital Supply Chain Transformation Frameworks and Supply Chain Resilience Strategy Theory. Thematic Mapping Model	AI, IoT connectivity, Big Data Analytics Operational resilience, supply chain visibility, transparency, agility, and process efficiency	Qualitative and exploratory research design	1. IoT shift supply chains from reactive to proactive, data-driven systems. 2. Real-world case data proves massive benefits: Unilever cut forecasting errors by nearly 15% using AI; Maersk utilizes IoT smart containers for real-time cold chain monitoring. 3.AI adoption has accelerated dramatically over recent years (shifting from 47% of businesses in 2018 to 72% in 2024).
3	Mutekwe et al., (2020).	RBV and Relational View	SCRM: Supply Chain Risk Information Sharing, Supply Chain Risk Analysis, Assessment, Supply Chain Risk-Sharing Mechanisms Operational Performance	quantitative survey design Primary data was collected via structured questionnaires from a sample of 227 food retail firm managers and supply chain professionals	1.The study found a significant positive relationship between SCRM and both risk information sharing and risk analysis and assessment 2.Strong positive relationships were observed between risk analysis and assessment and risk-sharing mechanisms 3.Risk-sharing mechanisms were found to significantly and directly predict operational performance
4	Ojochenem et al., (2026)	Dynamic Capabilities Theory (Teece et al., 1997)	(SCRM) RISI,RISA, RSMS, Risk Monitoring and Control Organisational Performance i.e Timely deliveries, Efficiency, Revenue stability	Cross-sectional survey design	1.Risk Identification significantly and positively affects performance and identified as the most critical driver. 2. Risk Assessment significantly and positively affects performance 3. Risk Mitigation Strategies significantly and positively affect performance 4. Risk Monitoring & Control significantly and positively affects performance
5	Paul Souma Kanti, et al. 2022	DOI (Rogers, 1995) & Technology-Organization-Environment TOE framework	Big Data Management Capability (Technological ERM Alignment (Organizational. Disruption Response (Environmental): A firm's historical exposure to negative exogenous shocks	Qualitative Pre-Testing: Unstructured verification interviews conducted with 9 senior industry Subject Matter Experts (SMEs) and 2 academic professors to refine item readability,	28-item instrument is proven to be structurally valid, stable, and highly reliable for analyzing corporate AI adoption determinants.
6	Sureshkumar, Narayanan et al., (2024)	Digital Transformation Models:	1.AI-Powered Risk Assessment in Supply Chains 2.Predictive Analytics and Machine Learning: 3.Natural Language Processing 4. Real-Time Monitoring and IoT Integration:	Qualitative empirical research design grounded in an interpretivist paradigm to capture real-world operational nuances.	1. Methodical Integration: Successful enterprises implement AI via localized pilot testing and progressive phase-ins to manage operational volatility. 2. Operational Efficiency: AI integration substantially accelerates hazard alerts, mitigates error rates, and improves response times compared to historical, human-led methods. 3. Structural Bottlenecks: due to internal data silos, a lack of trust due to complex un-auditable models, and intense initial deployment costs. 4. Strategic Accelerators: Overcoming deployment friction requires structured data governance, Explainable models, and modular, affordable architectures.
7	Attia Hussien Gomaa (2026)	Porter's Value Chain	(IoT telemetry, AI/ML analytics, Blockchain traceability, and Digital Twin simulations Human-machine collaboration).	SLR	Traditional SCRM models focus on isolated, single-tier risk types (supply, process, or demand) and completely miss cascading impacts within deep, multi-tier upstream networks. Purely automation-centric approaches often overlook human-centered, ethical, and environmental value creation, which are corrected by principles. Deploying an integrated, multi-module framework like SIRAF via DMAIC enables companies to transition from reactive friction to predictive, data-driven resilience .SMEs play an essential role in global supply chains but are highly vulnerable due to structural resource limitations in (VUCA) environments

8	Ngboawaji Daniel Nte (2026)	SCRM Dynamic Capabilities Theory 3. CAS Theory	Intelligence Management. Supply Chain Risk Mitigation / Supply Chain Resilience	sequential explanatory mixed-methods design	Evolution in maritime criminality towards armed robbery and theft, persistent infrastructure deficits that act as risk multipliers, and a critical “intelligence deficit” hindering proactive risk management.
9	Shirin Shahsavary, et al., (2026)	Predict-Then-Optimize Paradigm:	ML Input Features ML Discrete risk categories derived from the raw Fragile States Index (FSI).	A10-fold cross-validation model selection and evaluation scheme was employed	Feature driving metrics revealed that political/governance factors held the highest predictive power (~35% Gini importance), followed by social indicators (~24%) and economic metrics (~11%).
10	Rasha Aljaafreh (2026)	1.Supply Chain Management Theory & Practices: 2.Information Security Management 3.NIST (CSF	1.Core Technologies i.e Predictive Analytics, Big Data Analytics, Predictive Accuracy & Model Interpretability; Automated Decision-Making	1.SLR 2.PRISMA	1.91.4% of studies failed to combine real-time anomaly detection with longitudinal behavioural analysis. ML detects threats well, but BI is mostly reduced to retroactive dashboarding rather than forward-looking decision support 2. 61% of organizations reported being hit by supply chain cyberattacks in the prior year. Data breaches involving business partners cost roughly 12% more to fix
11	Fosso Wamba et al., (2024)	RBV & Dynamic capabilities Theory	BDAC-S BAC Organizational Outcomes: Customer	Empirical, quantitative, cross-sectional web-based survey design.	1.BDA-enabled sensing capability significantly and positively influences all structural outcomes: Customer Linking, Financial Performance, Market Performance, Strategic Business Value and Analytics Culture of Corporate Culture: Business Analytics Culture directly promotes Customer 3. Mediation Effect Confirmed that Business Analytics Culture serves as a critical mediator between sensing capabilities and Customer
12	A Systematic Review of AI-Driven Business Intelligence Architectures for Data-Informed Strategic Decision-Making Methods (2019–2026) American Journal of Advanced Technology and Engineering Solutions (March 2026)	Data-Driven / Data-Informed Decision-Making Theory: Models	AI Integration levels i.e. Real time processing capabilities. Mult model integration, AI operational techniques (Deep learning) Macro-level Oganisational performance i.e. Systems efficiency, Analytical precision,	Retrospective quantitative systematic review and structured bibliometric synthesis.	Based on Regional Disparities; Developed economies recorded system efficiency gains exceeding 30%, whereas developing regions achieved an average efficiency optimization of 21.5% due to baseline infrastructure disparities.
13	Ankush Reddy Sugureddy (2024)	BCP frameworks and Proactive Data Governance Models	NLP,AI-powered data analytics capacity, AI-driven predictive maintenance, AI architectures	MLR	1. Supervised Learning (30%) and Time Series Analysis (25%) are the most widely applied methods. 2. Neural Networks and Gradient Boosting deliver the highest classification precision. 3. Regression modeling shows AI-powered analytics has the strongest impact 4. NLP accelerates text-based risk analysis but exhibits a moderate direct impact on immediate continuity outcomes.
14	Stavros Kalogiannidis et al. (2024)	1.AI Algorithms and Machine Learning Models 2. NLP	NLP AI-powered data analytics, AI-driven predictive maintenance, Predictive risk assessment on business continuity. natural disasters, cyberattacks, and economic fluctuations	A cross sectional design and quantitative method was used.	1. AI applications, AI-driven predictive maintenance helps to reduce operational downtime. AI-powered predictive maintenance lowers the cost of equipment replacement and repair while extending the life of crucial equipment, both of which are essential for business continuity. 2. AI plays a critical role in event detection, management, and response, cybersecurity concerns.

15	Unearthing the barriers of Internet of Things adoption in food supply chain: A developing country perspective Shahbaz Khan et'al (2023)	Fuzzy Delphi Theory	IoT; Big data analytics, Wireless technologies, cloud computing Blockchain, FSC; Transparency, Traceability Reliability	Fuzzy Delphi method	The result of the FDM shows that twelve barriers are significant in the adoption of IoT in FSC. These barriers need to be mitigated in order to adopt the IoT in FSC to move towards sustainability. The supply chain managers, government and academia need to look at these barriers and proposed solutions to overcome them. 1.This study revealed barriers including the complex framework, IoT affordability, poor IT infrastructure, legal and regulatory standards, low awareness about IoT benefits, lack of skilled personnel, trust management, absence of knowledge management system, data heterogeneity, high investment and maintenance cost and IoT supplier scarcity. 2.The findings of this study are helpful for FSC managers to make their supply chain digitalised by overcoming these barriers. 3.Further, the policy planner could analyse their food supply chain in the context of the identified barriers to understand their cause so that they could better prepare themselves to adopt IoT.
16	Raisul Islam Khan1et al., (2025)	Complex ML algorithms, XGBoost, and gradient boosting models & multimodal artificial intelligence model	Supply Chain Risk Management Sensor Operational and External Intelligence, Multimodal datal intergration.	Mixed methods	The research demonstrates that the multimodal data integration system yields a significant improvement in predictive performance compared with classical single-source methods. The framework can provide a scalable and interpretable real-time risk assessment framework for the supply chain, with substantial implications in Industry 4.0 settings, where proactive risk management is essential for operational resilience.
17	Jack B. Reida et al., (2022)	EVDT	Decision support systems cloud computing, machine learning, economic analysis, complex systems modeling, systems engineering	Qualitative methods	EVDT-developed DSS support stakeholders in developing their own solutions. Ideally this means that individual stakeholders can directly handle and explore any simulations or models used, along with their underlying assumptions and structure.
18	Shiqi Qu, Xiangjiang Li, et'al (2025)	LLMs	Smart supply chain management business analytics, decision-making, risk management and collaborative integration.	SLR	1.Intrinsic drivers for smart supply chain development include globalised competition, efficiency demands, complexity requirements in the VUCA era, and technology-driven transformation opportunities. 2.Current barriers span four dimensions: information technology infrastructure, business analytics and decision-making, risk management, and collaborative integration
19	Dmitry Ivanov (2026)	ICARUS, Machine Learning, Neural Networks, Digital twin framework by Ivanov (2023), Simulation Models	A-SCDT; AI agents, human-AI collaboration, and digital twins. SCOM Data collection, Processing, Reasoning, and Integration	Simulation	1.Digital twins, model-based decision-support, and agen tic AI merge into A-SCDTs, driving a fundamental change in the role, use forms, deployment, and impact of optimisation and simulation in SCOM. Generative AI empowers managers to directly define LLM agents describing decision-making rules in a no-code, intuitive manner. Digital twins integrate network-wide data blended by analytics capabilities, creating up-to-date representations of physical supply chains. 2.The ICARUS framework provides the following implications; Interaction: manager and model interact with each other using agent and GenAI • Creativity is the ability of improvisation– AI-assisted modelling • Adaptation: data-driven model adjustments • Reasoning is the ability to analyse, plan and make decisions, predict, and detect anomalies • Ubiquity– interoperability, real-time and ubiquitous access • Synchronization–ability to integrate data and orchestrate agent actions 3.The A-SCDT was theorised as a distinct and novel area of practical and theoretical importance, proposing a framework of how agentic AI and digital technology can help in SCOM decision support and decision-making. The ability to create self-service, interactive analytics enabling rapid model development and triggering the shift towards iterative decision-making support, real-time adaptability and predictive insights, data synchronisation, ubiquitous access, and AI-supported reasoning was emphasised. 4.In the case of missing data points, high energy and computational costs, reasoning inconsistencies and non-deterministic responses, ethical, societal, legal, and governance challenges, and cybersecurity issues should be considered.

20	Ilya Jackson et al., (2024)	RBV & Dynamic Capabilities	GAI capabilities; Learning, Perception, Prediction, Interaction, Adaptation, Reasoning, and Artificial 'Creativity' SCOM decision-making domains	Qualitative methodology	Capability Enhancement: Proves that GAI elevates traditional AI by generating synthetic data to solve information scarcity, simulating complex future risk scenarios, and enabling context-rich conversations. Managerial Application provides a practical tool allowing practitioners to assess internal operations, prioritize AI technology investments, and target talent upskilling. The Economic Impacts Connect macro-productivity gains to cognitive task automation, highlighting that GAI can drastically boost organizational resilience and total market output.
21	Seyed Ashkan Hosseini Shekarabi et al., (2025)	Dynamic Capability theory, RFPN & KCON Analysis, PRISMA	Supply Chain Resilience; Readiness, response, and recovery Risk mitigation;	PRISMA	1.KCON analysis enabled us to identify the most frequently occurring keywords in the literature and their interrelationships, revealing the field's most salient themes and patterns 2.Developing supply chain resilience presumes that businesses can rapidly recover from disruptions by either returning to regular operations or advancing to a higher level of operational efficiency 3. Automation, predictive analytics, collaboration tools, AI, and ML can all be used to raise the efficiency and effectiveness of the supply chain management process, which the relations among keywords emphasise in this statement. Therefore, turning to ML, the application of ML algorithms has been highlighted as a possible means of enhancing supply chain management processes.
22	Lutfor Rahman et al., (2026)	UBI framework	AI-Driven Predictive Analytics; Sensor streams, Transaction records, and Macroeconomic indicators Supply Chain Resilience; post pandemic freight volatility, and climate-driven logistics shocks	Quantitative methodology was used	1.In supply chain management, the framework reaches 94.1% disruption-prediction accuracy, a 22.9 percentage-point lift over domain-specific baselines and pulls demand-forecast MAPE down from 12.4% to 7.8%. In financial risk, ensemble-transformer hybrids deliver an AUC-ROC of 0.93 on portfolio stress testing and an F1 of 91.4% on credit-risk classification. 2. In marketing, AI-orchestrated cross-domain targeting raises campaign ROI from 14.2% to 45.3%, and churn-prediction recall climbs from 68.0% to 84.7%.
23	Anas Iftikhar et al., (2022)	TAM, TOE framework, or unified theory of acceptance and Use of Technology (UTAUT)	Digital innovation; IoT, blockchain technology, BDA, and AI, Additive Manufacturing, (Xu et al., 2018; Strozzi et al., 2017; Ali & Aboelmaged, 2022) Supply Chain Resilience;	Mixed methods	1.It was discovered that innovative technologies (big data analytics, IoT, Industry additive manufacturing, blockchain, artificial intelligence, etc.), supported data analytics can play a significant role in anticipating disruptive events, reducing their impacts and assuring business continuity. 2.The researcher found that IoT facilitates the design of intelligent and robust SCs by enabling real-time information exchange, and improved cooperation among business partners in the network.
24	Emmanuel Susitha et al., (2024)	DCV & RBV	Supply Chain Competitivenes; SCA, SCCP & DT	Mixed methods & Bibliometric analysis, PRISMA framework.	1.The study suggests that the context of SCA, SCCP, and DT is driven mainly by empirical, data-centric approaches that facilitate statistical analysis and generalizable findings 2. Bibliometric and network analyses reveal interconnected themes and areas of dense academic interest, such as agility, technology, performance, and competitiveness, alongside emerging fields of study. 3. Core themes and areas of interest within the joint field of SCA, SCCP, and DT, such as supply chain, agility, performance, manufacturing, and technology, were identified through co-occurrence and keyword frequency analysis. While extensively studied, these themes still present emerging areas that warrant further exploration. 4. Similarly, Johnson and Onwuegbuzie [62] argue that by combining the quantifiable precision of quantitative methods with the contextual depth of qualitative methods, mixed-methods research can provide richer insights

25	Atoapem Frimpong Barimah (2024)		Supplier Risk Management; Supplier evaluation, Payment terms, Contract duration, Buyer-supplier collaboration Supplier risks IN Procurement; Production delays, Quality issues, Financial challenges.	Systematic Literature review approach	The chosen articles reviewed ranged from 2020 to 2023. 1.The analysis revealed insights the key themes of interest for this review, including risk identification, assessment, and mitigation strategies. The specific elements delved into are supplier evaluation, payment terms, contract duration, and buyer-supplier collaboration to provide a comprehensive understanding of the field. 2. The review highlights the importance of collaboration with supply chain partners to implement effective risk management processes. 3. Supplier evaluation is critical in assessing and approving suppliers based on their ability to meet organizational needs, this ensures the procurement of quality goods and services at competitive prices. 4. Payment terms significantly affect supplier risk, including financial, credit, currency, market, counterparty, and settlement risks. Timely payment settlement is essential for reducing financial uncertainties for suppliers, thus enhancing supply chain stability. 5. Buyer-Supplier Collaboration fosters supply chain transparency, efficiency, and trust, thereby reducing operational risks.
26	Shireen Al-Hourani (2025)	PRISMA Framework	AI/ML; Demand forecasting, Inventory Optimization, PSC Functions; Agile flexibility, Collaborative visibility,	Systematic Literature review approach	1.The findings reveal that despite AI/ML's promise, significant research gaps persist. Particularly, AI/ML-driven regulatory compliance and real-time supplier collaboration remain underexplored. Over 59.3% of studies fail to address regulatory frameworks and ethical considerations. 2.In addition, major challenges emerge such as the limited real-world deployment of AI/ML-driven solutions and the lack of managerial impacts on PSC resilience. This study emphasizes the need for stronger regulatory frameworks, broader empirical validation, and AI/ML-driven predictive modelling.
27	Identifying risks in sustainable procurement for construction: a systematic literature review and text-mining approach. Olabode Emmanuel Ogunmakinde (2025)	PRISMA Framework	Sustainable Procurement; Integration challenges, Supplier coordination, Supply Chain Risk in Construction; Cost increase, Project delays, Long term saving	Systematic literature review and Collocation based Text-mining analysis.	1.The analysis identified fifteen key risk indicators clustered around five major themes: financial risks, project management challenges, design and material selection issues, procurement and supply chain risks, and stakeholder-related barriers. Notably, the study highlights a lack of integrated risk management strategies that align with sustainability goals in construction procurement. 2. Furthermore, Song et al. (2017) discussed the increasing emphasis on green procurement and its correlation with operational and financial performance. However, it is crucial to note that not all green procurement activities directly translate to economic benefits, underscoring the need for strategic decision-making in this domain. It is evident that while sustainable and green procurement practices hold immense potential, they are not without challenges.
28	Dengyuhui Li (2023)	PESTEL Framework	Maritime transportation resilience; resilience measurement, resilience evaluation, Maritime Risks; Adverse weather conditions, Labor strikes, and Infrastructure failure.	Descriptive statistical analysis, Bibliometric analysis, and Literature review	1.Disruptions also affect the movement of cargoes and empty containers, which are considered in clusters. The effective management of empty containers is crucial for both economic effects and sustainability impacts 2. Among these papers, two papers with a burst period before 2014 to build the research foundation consider container liner shipping networks without uncertainties or supply chain disruptions without incorporating the characteristics of maritime transportation. 3.Five papers with a burst period until 2018 focus on more resilience issues and methods in maritime transportation. Three papers are published in recent years with more comprehensive and in-depth discussions in this field that remain influential till now.

29	Kumar, et al., (2023)	Relation View Theory	SCR; Sustainability, Agile management, Artificial Intelligence Supply Chain Management	1.Bibliometric review; 336 articles published between 2011 and 2021 were retrieved in Scopus for this bibliometric analysis 2.Exploratory research	1.The author found that supply chain risk management, sustainability, agile management, artificial intelligence and block chain are trending topics 2.The numerous frameworks and methods for SCR evaluation and improvement that have been developed by academics have highlighted the need for a thorough and proactive approach to tackling supply chain risks. 3. It was observed that SCR may be impacted by a variety of variables, including halts, hazards and vulnerabilities connected to distribution, inventory, production and transportation. 4.There is growing interest in employing technology to enhance SCR.
30	Iyadunni Adewola Olaleye et al., (2024)	Predictive Algorithms, Control Tower model, Machine learning Algorithms, Digital Twin model.	Supply Chain Resilience; Real time monitoring, Demand forecasting, Risk Assessment and Monitoring; Adaptability, Responsiveness, and Recovery	Descriptive analysis	1.The transformative role of predictive analytics and data-driven strategies in building resilient supply chains is becoming increasingly evident as companies strive to navigate a complex and volatile global market. Predictive analytics enables organizations to anticipate and adapt to disruptions by providing insights that inform proactive decision-making, enhance operational flexibility, and optimize resource allocation. 2. Demand forecasting, enhanced through machine learning, enables firms to prepare for market fluctuations and consumer behavior shifts, mitigating the risks of overstocking or stockouts 3. Fostering a culture that values data-driven decision-making will enable organizations to overcome internal resistance to new technologies. Encouraging cross-functional collaboration, providing data literacy programs

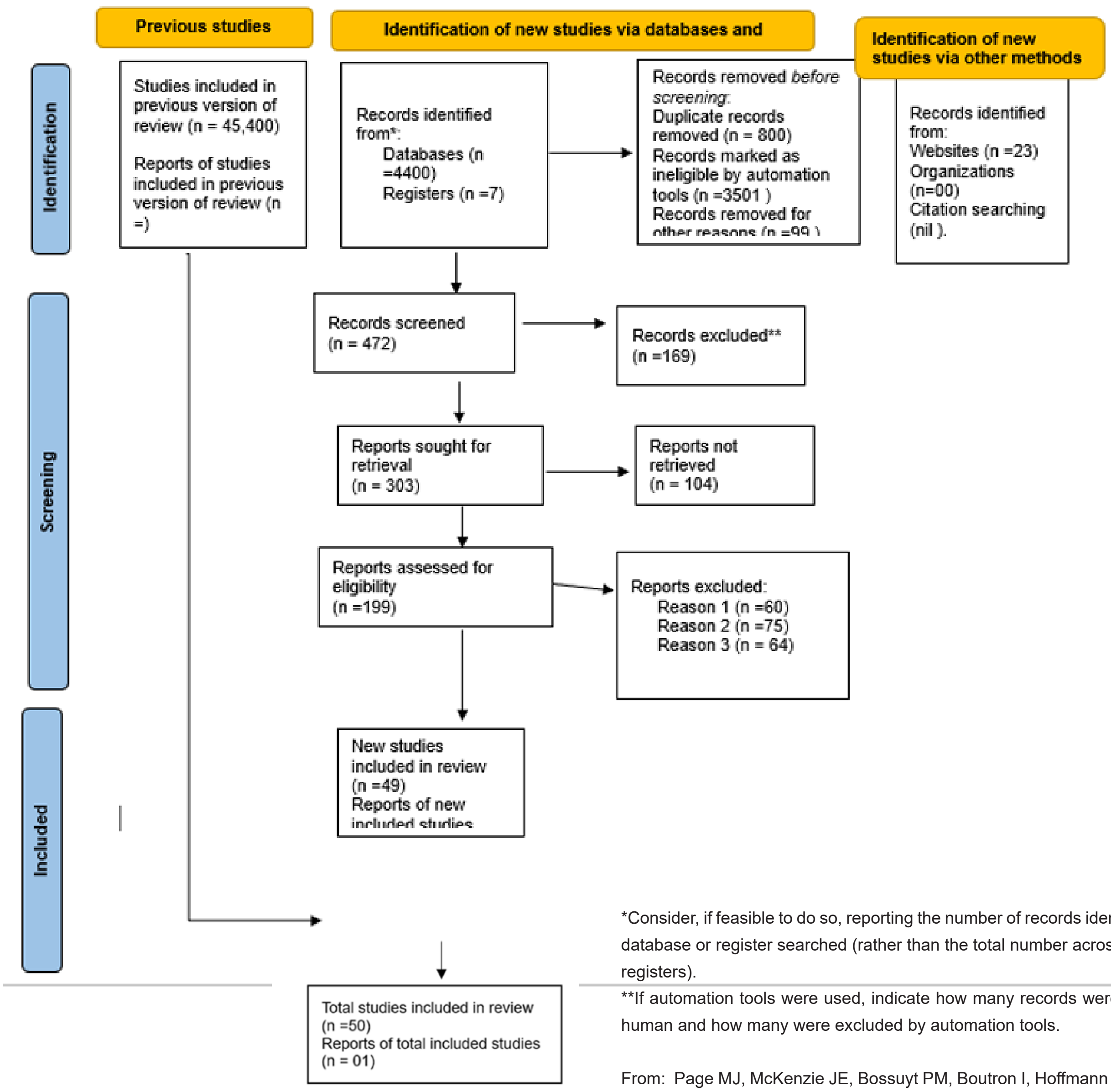
LIST OF ACRONYMS

AI - Artificial Intelligence,
A-SCDT - Agentic supply chain digital twin
BCP - Business Continuity Planning,
BDA - Big Data Analytics, Data Analytics-enabled Sensing Capability
CAS - Complex Adaptive Systems,
CSF - Cybersecurity Framework,
DMAIC - Define, Measure, Analyze, Improve, Control,
DEMATEL - Decision-Making Trial and Evaluation Laboratory,
DOI - Diffusion of innovation theory,
ERM - Enterprise Risk Management,
EVDT - The Environment-Vulnerability-Decision-Technology Framework,
FDM - Fuzzy Delphi Method
ICARUS - Interaction, Creativity, Adaptation, Reasoning, Ubiquity, and Synchronization,
IOT adoption, Internet of Things,
GAI - Generative artificial intelligence,
SCRM - Supply Chain Risk Management
SCOM - Supply Chain and Operations Management
MLR - Multiple Linear Regression Model,
ML - Machine Learning
RFPN - Research Focus Parallels Network (Maps the connectivity among research streams)
KCON - Keyword co-occurrence network (Analyses the frequency and interrelationships among key terms)
PRISMA - Preferred Reporting Items for Systematic Reviews and Meta-Analyses.
UBI - Unified Business Intelligence framework
HOMALS - Homogeneity Analysis using Alternating Least Squares
SLR - Structured literature review
MCA - Multiple Correspondence Analysis
DCV - Dynamic Capability View
RBV - Resource Based View
SCA - Supply Chain Analytics
SCCP - Supply Chain Competitiveness
DT - Digital Technologies
SRM - Supplier Relationship Management
PSC - Pharmaceutical Supply Chains
PESTEL - Political, Economic, Social, Technological, Environmental and Legal Considerations.
PRISMA - Preferred Reporting Items for Systematic reviews and Meta - Analyses,
SCR - Supply Chain Resilience
A-SCDT - Agentic – Supply Chain Digital Twins
TAM - Technology Acceptance Model
TOE - Technology Organization Environment
VUCA - volatile, uncertain, complex, and ambiguous
SIRAF - Strategic Integrated Risk Assessment Framework,

Methodology

This paper has adopted a systematic review methodology using a PRISMA. A google search made on 07th July, 2025 brought 454,000 results, some of these are suitable candidates for this study while others were rubble hiding important results and discussion, some were excluded on further scrutiny. This study implores the SLR to unearth and offer a bigger lens with which to view the supply chain risks.

This furnishes useful evidence and draws evidence-based conclusions. A pre-set protocol was used with the aid of PRISMA to select candidates for the study as shown in figure 2



*Consider, if feasible to do so, reporting the number of records identified from each database or register searched (rather than the total number across all databases/ registers).

**If automation tools were used, indicate how many records were excluded by a human and how many were excluded by automation tools.

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71. For more information, visit: http://www.prisma-statement.org/

Figure 2 A PRISMA diagram on how studies were selected

Understanding the role of SCI in risk mitigation requires first understanding the nature of the risks that SCI is intended to address. This section develops a taxonomy of supply chain risks confronting manufacturing firms in Uganda, organised across three interacting layers: operational, infrastructural, and environmental-institutional risks. The taxonomy draws on the global supply chain risk management literature and the limited but growing body of empirical work specific to Uganda and East Africa.

Operational risks are the most immediate and frequently encountered category of supply chain disruptions for Ugandan manufacturers. These risks arise from the day-to-day functioning of procurement, production, and distribution processes and include supplier insolvency or non-performance, lead-time variability, inventory stockouts, and product quality failures.
The operational risk profile of Ugandan manufacturing is shaped by several structural characteristics that differentiate it from developed-economy contexts. First, Uganda's manufacturing sector is heavily dependent on imported raw materials and intermediate goods, with a significant portion of inputs sourced from Asia and the Middle East (Olwor, 2023). This import dependency creates long and fragile supply lines in which a single disruption — a shipping delay, a port congestion event, or a foreign exchange shortage — can cascade into a complete production halt. Second, the supplier base

available to Ugandan manufacturers is thin, with limited alternatives when a primary supplier fails. In contrast to developed-economy manufacturers who can typically draw on competitive supplier markets, Ugandan firms often operate in supplier-constrained environments where the costs of switching are prohibitively high (Tukamuhabwa et al., 2023).

Third, limited working capital and restricted access to trade credit mean that Ugandan manufacturers cannot maintain the buffer inventories that serve as a first line of defence against supply variability in developed contexts (Alinda et al., 2023). The financial constraints interact with operational risks in a mutually reinforcing cycle: a supply disruption depletes cash reserves, which in turn reduces the firm's ability to invest in risk mitigation measures, increasing vulnerability to the next disruption.

(Chari et al., 2020) document analogous patterns in humanitarian supply chains in Southern Africa, where supply disruptions are amplified by the same structural factors — import dependency, limited supplier alternatives, and financial constraints — that characterise Ugandan manufacturing supply chains. The humanitarian context, while distinct in its operational objectives, provides transferable evidence on how supply chain risk dynamics operate in resource-constrained African environments.

Infrastructural risks constitute the binding constraint on both supply chain performance and SCI adoption in Uganda. These risks arise from deficits in the physical and digital infrastructure that supports supply chain operations and include unreliable transport networks, intermittent electricity supply, and limited information and communication technology (ICT) penetration.

Uganda's transport infrastructure presents persistent challenges for manufacturing supply chains. Road networks connecting manufacturing hubs to markets and ports are characterised by variable quality, with significant deterioration during rainy seasons and chronic congestion at key nodes such as the Kampala-Malaba corridor (Lugada et al., 2022). Rail infrastructure, which could provide a lower-cost alternative for bulk transport, remains underdeveloped and unreliable. The combination of road dependency and road unreliability creates unpredictable lead times that complicate inventory planning, production scheduling, and customer delivery commitments.

Energy intermittency is a particularly acute risk for manufacturing operations. Uganda's electricity grid, while improving in coverage, experiences frequent outages and voltage fluctuations that disrupt production processes, damage sensitive equipment, and create uncertainty about production capacity (Pius & Owin, 2024). The cost of backup generation — typically diesel generators — adds a significant financial burden that erodes the competitiveness of Ugandan manufacturers relative to counterparts in countries with more reliable grid infrastructure.

ICT gaps compound the transport and energy challenges. While mobile phone penetration in Uganda is relatively high, access to the reliable broadband internet connectivity required for cloud-based SCI platforms, real-time data transmission, and IoT sensor networks remains limited, particularly outside the Kampala metropolitan area (Pius & Owin, 2024). The digital divide is not merely a matter of infrastructure availability but extends to digital literacy and the organisational capacity to manage and interpret data — a theme explored further in Section 5.

These infrastructural risks interact with operational risks in ways that amplify the overall risk exposure of Ugandan manufacturers. A transport delay, for example, is not an isolated event but one that cascades into inventory depletion, production stoppage, and customer dissatisfaction, with the cascade accelerated by the absence of the buffer mechanisms — safety stock, alternative transport modes, and flexible production capacity — that cushion disruptions in developed-economy supply chains.

Environmental and Institutional Risks: Regulation, Currency, and Climate Shocks

The third layer of supply chain risk confronting Ugandan manufacturers comprises environmental and institutional factors that operate at the macro level and are largely beyond the control of individual firms. These include regulatory volatility, exchange-rate fluctuations, climate-related disruptions, and political instability.Regulatory risk in Uganda manifests through frequent changes in tax policy, import duties, and licensing requirements that create uncertainty for manufacturers reliant on cross-border supply chains (Alinda et al., 2023). The East African Community's trade harmonisation efforts have partially mitigated some of these risks, but the implementation gap between regional agreements and national enforcement remains substantial. Manufacturers operating across multiple East African markets must navigate divergent regulatory regimes while managing the supply chain implications of each regulatory change.

Currency volatility represents a pervasive and persistent risk. The Ugandan shilling has experienced significant depreciation against major trading currencies over the past decade, creating unpredictable cost structures for manufacturers dependent on imported inputs. (Okoye et al., 2024) identify currency risk as a critical factor in international supply chain risk management, noting that the impact is disproportionately severe for firms in developing economies that lack access to hedging instruments and have limited pricing power to pass cost increases to customers.

Climate-related risks are increasingly salient for Ugandan manufacturing. The country's agricultural processing sector — a significant component of Uganda's manufacturing base — is directly exposed to climate variability through its dependence on agricultural raw materials (Ssennoga et al., 2019). Floods, droughts, and changing rainfall patterns disrupt both the availability and the quality of agricultural inputs, creating supply chain risks that propagate through processing, distribution, and export channels. (Adelhardt & Berneiser, 2024) provide evidence from agrivoltaic projects in sub-Saharan Africa that climate risk interacts with energy risk in ways that demand integrated risk assessment frameworks.

Political stability in Uganda has been maintained relative to several neighbouring countries, but regional instability — particularly in South Sudan and the eastern Democratic Republic of Congo — creates spillover risks through trade disruption, refugee flows, and the diversion of government resources from infrastructure investment to security expenditure. (Chari & Ngcamu, 2017) demonstrates how disaster risks, including those with political dimensions, propagate through supply chains in ways that are difficult to predict and insure against.

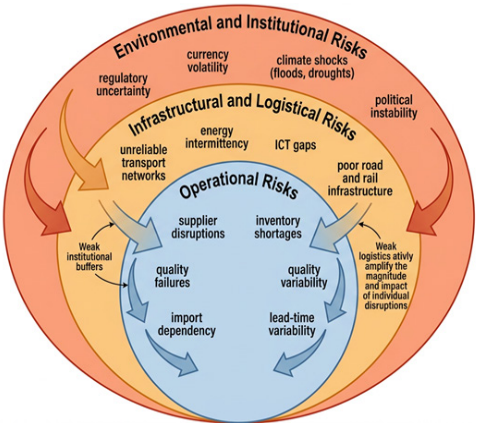


Figure 3. Three-layer risk typology for Ugandan manufacturing supply chains

The three risk layers, illustrated in Figure 3, do not operate in isolation. They interact through compounding mechanisms in which an infrastructural failure (e.g., a power outage) triggers an operational disruption (e.g., production stoppage), which is then exacerbated by an institutional constraint (e.g., the absence of business interruption insurance). This compounding dynamic is the defining characteristic of supply chain risk in Uganda's manufacturing context and the primary challenge that SCI must address.

SCI-Driven Risk Mitigation: Strategies, Mechanisms, and Evidence

Having established the conceptual foundations of SCI and the risk landscape of Ugandan manufacturing, this section examines the evidence on how SCI capabilities translate into risk mitigation outcomes. The analysis is organised around three complementary pathways: early warning and disruption detection, decision agility and intelligence-to-action conversion, and organisational learning and adaptive resilience.

Early Warning and Disruption Detection Through SCI

The most direct mechanism through which SCI contributes to risk mitigation is by reducing the time between the emergence of a supply chain threat and its detection by the affected firm. In the absence of systematic intelligence, disruptions are typically detected through downstream symptoms a missed delivery, a customer complaint, or a production stoppage at which point the disruption has already materialised and the response options are limited to reactive damage control.

SCI-enabled early warning systems aim to shift detection upstream, identifying emerging threats before they cascade into operational disruptions. (Brintrup et al., 2019) demonstrate that machine learning models trained on supplier performance data, financial indicators, and external risk signals can predict supplier disruptions with sufficient lead time to enable proactive mitigation including alternative sourcing, inventory rebalancing, and production rescheduling. The detection-to-response gap, measured as the time between the first signal of an emerging disruption and the initiation of a mitigation response, is the critical performance metric for early warning systems.

(Dou et al., 2024) extend this logic to closed-loop supply chains, showing that predictive models incorporating production cost, disruption cost, and reliability parameters can identify high-risk nodes and evaluate the cost-effectiveness of alternative mitigation strategies. Their framework demonstrates that the value of early warning is not uniform across all supply chain configurations but is contingent on the structure of the supply network, the cost of disruptions, and the availability of feasible mitigation options.

For Ugandan manufacturers, the reliability of SCI-enabled early warning is constrained by the sparsity and latency of available data streams. While developed-economy early warning systems draw on rich, real-time data from IoT sensors, ERP systems, and external data feeds, the data environment in Uganda is characterised by manual record-keeping, fragmented information systems, and limited supplier data-sharing (Pius & Owin, 2024). The implication is not that early warning is impossible in Uganda's context but that it must be designed around the data that is available which may mean relying on a smaller set of leading indicators, accepting longer detection lags, and targeting the highest-impact disruption categories rather than attempting comprehensive coverage.

Decision Agility: Intelligence-to-Action Conversion in Risk Responses

The value of SCI for risk mitigation is realised not in data collection but in the conversion of intelligence into agile decisions. Decision agility refers to the speed and quality with which firms respond to risk signals, and it depends on two factors: the timeliness and accuracy of the intelligence received, and the organisational decision-making structures that translate intelligence into action (Yang et al., 2021).

The relationship between intelligence quality and decision quality is mediated by the firm's decision-making architecture. (Dubey et al., 2017) demonstrate that supply chain visibility improves sustainable performance only when combined with organisational capabilities that enable the effective use of visibility data. Visibility without the capacity to act on it generates information overload without corresponding improvements in risk outcomes. (R. et al., 2023) provide evidence from two empirical studies that supply chain visibility enhances cyber-resilience through the mediating mechanism of absorptive capacity — the firm's ability to recognise, assimilate, and apply external knowledge.

The speed-quality trade-off in disruption response decisions is a central tension in SCI-driven risk mitigation. SCI can accelerate decision-making by providing pre-analysed intelligence that reduces the cognitive burden on decision-makers. However, the pressure to respond quickly can lead to premature closure — decisions made before sufficient intelligence has been gathered and analysed. (Ivanov & Dolgui, 2020) address this tension through the concept of the digital supply chain twin, which enables decision-makers to simulate the consequences of alternative response strategies before committing to a course of action, thereby reducing the risk of hasty decisions without sacrificing response speed.

In the Ugandan context, decision agility is shaped by organisational factors that are distinct from the technological infrastructure of SCI. Manufacturing firms in Uganda, particularly small and medium enterprises (SMEs), tend to have concentrated decision-making authority, limited formal risk management processes, and a reliance on experiential rather than analytical decision-making (Asamoah et al., 2020). These organisational characteristics do not preclude the use of SCI but they shape how intelligence is received, interpreted, and acted upon a theme that the contextual-fit dimension of the analytical framework captures.

Organisational Learning and Adaptive Resilience from Post-Disruption Intelligence

The third pathway through which SCI contributes to risk mitigation is organisational learning the use of post-disruption intelligence to strengthen supply chain design, improve preparedness, and reduce vulnerability to future disruptions. This pathway operates on a longer time horizon than early warning and decision agility, and its effectiveness depends on the firm's capacity to institutionalise the lessons extracted from disruption experiences. SCI supports organisational learning by providing the analytical infrastructure for post-disruption review. Rather than relying on anecdotal accounts of what went wrong, firms with SCI capability can conduct data-driven post-mortems that trace the causal chain from the initial disruption signal through to the final operational impact, identifying the points at which detection, decision, or response could have been improved (Dubey et al., 2019). This analytical capability enables the transition from experience-based to evidence-based learning, in which the lessons from one disruption are systematically captured and applied to strengthen the supply chain's design and preparedness.

The absorptive capacity of the firm its ability to recognise the value of new external information, assimilate it, and apply it to commercial ends is the critical mediating variable in the relationship between SCI and organisational learning (R. et al., 2023). Firms with high absorptive capacity are able to extract actionable lessons from post-disruption intelligence and translate them into structural improvements in supply chain design. Firms with low absorptive capacity, by contrast, may collect post-disruption data without converting it into learning, repeating the same patterns of vulnerability in subsequent disruptions.

Queiroz et al., 2021 provide evidence from the COVID-19 pandemic that supply chain resilience in emerging economies is built through a combination of reactive learning adapting to disruptions as they occur and proactive investment in flexibility and redundancy. The firms that emerged strongest from the pandemic were those that combined real-time intelligence on disruption evolution with the organisational capacity to reconfigure their supply chains in response to that intelligence.

Table 3. SCI-driven risk mitigation pathways and their applicability to Ugandan manufacturing

Pathway	Mechanism	Key enabler	Uganda-specific constraint
Early warning	Upstream detection of emerging threats	Multi-source data fusion (Brintrup et al., 2019)	Data sparsity and latency; limited sensor infrastructure
Decision agility	Rapid intelligence-to-action conversion	Decision-support systems; digital twins (Ivanov & Dolgui, 2020)	Concentrated decision authority; experiential decision norms
Organisational learning	Post-disruption analysis and adaptation	Absorptive capacity; institutional memory (Dubey et al., 2019)	Limited formal risk management processes; high staff turnover

Table 3 summarises the three pathways, their mechanisms, key enablers, and the Uganda-specific constraints that moderate their effectiveness. The table highlights a recurring pattern: the pathways are conceptually sound and supported by evidence from developed-economy contexts, but their application in Uganda is constrained by factors — data availability, organisational structure, and institutional capacity — that are not captured by the global SCI literature. This pattern reinforces the centrality of the contextual-fit dimension in the analytical framework.

Figure 4. Pathways of SCI-driven risk mitigation

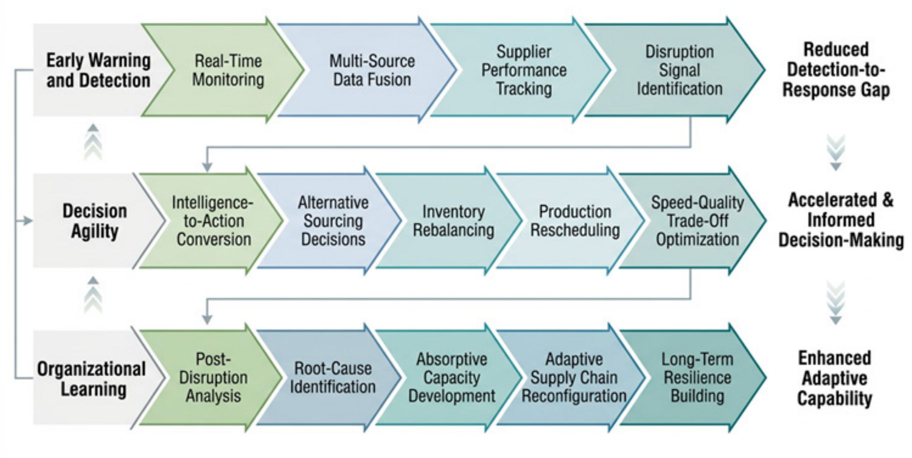


Figure 4 depicts the three pathways and their interconnections. The feedback loop from organisational learning to improved early warning and decision agility is the mechanism through which SCI creates compounding improvements in risk mitigation capability over time. Each disruption cycle, when properly analysed, strengthens the intelligence infrastructure for the next cycle.

SCI Adoption Barriers and Enablers in Developing-Country Manufacturing

The preceding sections have established that SCI offers genuine potential for improving risk mitigation outcomes in manufacturing supply chains. This section shifts focus from potential to practice, examining the barriers that constrain SCI adoption in developing-country manufacturing contexts and the enablers that can facilitate adoption despite these constraints.

Technological and Infrastructural Barriers to SCI Adoption

The technological barriers to SCI adoption in Uganda are not merely a matter of hardware availability but reflect a deeper digital ecosystem gap that encompasses connectivity, interoperability, and data standardisation. (Pius & Owin, 2024) identify unreliable power supply, limited internet connectivity, and the high cost of IoT and analytics platforms as the primary technological constraints on AI and data-driven supply chain management in Uganda. These constraints are not independent: the unreliability of power supply undermines the continuous operation of IoT sensors and data servers, while limited internet connectivity restricts the transmission of data to cloud-based analytics platforms.

The digital ecosystem gap extends beyond physical infrastructure to the software and data layers of the SCI stack. Interoperability between different enterprise systems — ERP, warehouse management, and transportation management — remains a significant challenge, with many Ugandan manufacturers using fragmented, non-integrated software solutions or relying on paper-based records (Alinda et al., 2023). The absence of data standards across supply chain partners further complicates data integration, as each supplier and logistics provider may use different formats, identifiers, and data quality standards.

The informal nature of many supply chain relationships in Uganda adds a further layer of complexity. When transactions are conducted through personal relationships, verbal agreements, and cash payments, the data trails that SCI depends on are thin or non-existent. (Asamoah et al., 2020) demonstrate that social network relationships among SMEs in developing economies can enhance supply chain resilience, but these relationships operate through mechanisms — trust, reciprocity, and information sharing — that are not easily captured by formal SCI systems.

Organisational and Financial Constraints: Capability, Awareness, and Investment. Organisational capability gaps are the primary internal barrier to SCI adoption in Ugandan manufacturing, and they are arguably more binding than financial constraints. The gap has two dimensions: awareness and skills. Managerial awareness of SCI — what it is, what it can achieve, and how it differs from conventional supply chain management — is limited among Ugandan manufacturers, particularly SMEs (Olwor, 2023). Without awareness of the potential benefits, SCI is unlikely to be prioritised in resource allocation decisions, regardless of the availability of funds.

The skills dimension encompasses data literacy, analytical capability, and the capacity to manage technology-intensive supply chain processes. (Tukamuhabwa et al., 2023) find that supply chain integration in Uganda's wooden furniture industry is constrained by limited technical capability and the absence of specialised supply chain management skills. The skills gap is not unique to Uganda it is a common challenge across developing-economy manufacturing sectors but it is particularly acute in contexts where the educational and vocational training systems have not yet adapted to the data and analytics demands of modern supply chain management.

Financial constraints, while real, operate primarily through their interaction with organisational capability gaps. The capital investment required for SCI adoption including hardware, software, and implementation services is substantial relative to the financial resources of most Ugandan manufacturers. (Saidi et al., 2021) note that the cost of building resilient supply chains in emerging economies is a significant barrier, particularly when the return on investment is uncertain and the payback period is long. However, the financial barrier is mediated by awareness: firms that understand the value of SCI are more likely to allocate scarce capital to intelligence investments, while firms that lack awareness will allocate capital to more familiar, lower-risk investments regardless of the potential returns from SCI.

The contrast between large manufacturers and SMEs is stark. Large manufacturers with multinational operations or export-oriented production may have access to the capital, skills, and technology partnerships needed to adopt SCI (James et al., 2025). SMEs, which constitute the majority of Uganda's manufacturing firms, lack these resources and face a fundamentally different adoption calculus. The SCI solutions that are designed for large enterprises — with their assumptions of dedicated IT staff, reliable infrastructure, and integrated systems — are unlikely to be appropriate for the SME context.

Despite the substantial barriers identified above, there are enabling factors and adoption pathways that offer a more feasible route to SCI adoption for Ugandan manufacturers than attempting to replicate the full-stack technology deployments typical of developed-economy firms. These enablers operate at multiple levels: technological, organisational, and institutional. At the technological level, mobile-based platforms represent the most promising entry point for SCI in Uganda. Mobile phone penetration exceeds 70% in Uganda, and mobile money platforms have demonstrated that sophisticated digital services can be delivered through mobile infrastructure even in the absence of widespread broadband connectivity (Pius & Owin, 2024). Mobile-based SCI applications — including SMS-based supplier performance tracking, mobile-optimised inventory management dashboards, and WhatsApp-based logistics coordination — can provide a foundation of descriptive intelligence that requires minimal additional infrastructure investment.

At the organisational level, incremental adoption pathways that start with low-cost, low-complexity SCI tools and progressively build capability are more realistic than attempting a single-step transformation. (Saidi et al., 2021) propose a holistic framework for building sustainable resilient supply chains in emerging economies that emphasises phased implementation, starting with the most accessible capabilities — basic data collection and descriptive analytics — and advancing toward predictive and prescriptive intelligence as organisational capability and data infrastructure mature. This incremental approach aligns with the analytical maturity spectrum described in Section 2.3: the goal is not to leap from no intelligence to prescriptive analytics but to move one step up the ladder at a time.

At the institutional level, public-private data partnerships, industry association initiatives, and government-led digital infrastructure programmes can reduce the cost and risk of SCI adoption for individual firms. (Ngum et al., 2022) describe the East African Community's regulatory harmonisation programme as a model for regional cooperation that reduces the institutional barriers to cross-border supply chain integration. Similar collaborative models could be applied to supply chain data-sharing, with industry associations or government agencies providing the data infrastructure and governance frameworks that individual firms cannot develop independently.

(Lawrence & Mupa, 2024) document innovative approaches to logistics enhancement in East Africa, including lean strategies adapted to the region's specific infrastructural conditions. These approaches demonstrate that context-adapted innovation — rather than wholesale technology transfer — is the more effective route to supply chain improvement. The same principle applies to SCI: the most effective SCI tools for Ugandan manufacturers will be those designed for Uganda's specific conditions, not those imported from contexts with fundamentally different infrastructural and institutional baselines.

Conclusion and recommendations

This review has examined the role of supply chain intelligence in risk mitigation within Uganda's manufacturing sector, evaluating the evidence through a three-dimensional analytical framework encompassing risk visibility, decision agility, and contextual fit. The synthesis yields three principal conclusions. First, SCI offers genuine potential for improving risk mitigation outcomes in Ugandan manufacturing. The conceptual foundations of SCI such as data acquisition, integration, analysis, and dissemination are generalisable across contexts, and the mechanisms through which SCI translates into risk mitigation early warning, decision agility, and organisational learning are supported by a growing body of evidence from developed-economy manufacturing. The analytical maturity spectrum from descriptive to prescriptive intelligence provides a structured pathway for capability development that is applicable to Ugandan manufacturers, with descriptive intelligence representing an accessible entry point that can be supported by mobile-based tools and existing data infrastructure.

Second, the effectiveness of SCI in Uganda is contingent on the alignment between intelligence tools and local institutional and infrastructural realities. The barriers to SCI adoption — technological, organisational, financial, and institutional — are substantial and interact in ways that create a capability gap between the SCI tools available in the global market and the conditions under which Ugandan manufacturers operate. The contextual-fit dimension of the analytical framework is therefore not a secondary consideration but the primary determinant of whether SCI investments will yield the risk mitigation benefits that the literature promises.

Third, the evidence base for SCI effectiveness in developing-country manufacturing is characterised by a critical gap between the volume of developed-economy research and the near-absence of primary empirical studies grounded in Uganda. This gap means that the conclusions of this review — and the policy and practice recommendations that flow from them — rest on conceptual extrapolation and indirect evidence rather than direct causal evidence from Uganda's manufacturing context.

Research Gaps

This section steps back from the substantive findings of the review to critically evaluate the state of the evidence on which those findings rest. The assessment identifies three major research gaps and evaluates the evidence hierarchy across the reviewed literature.

The most significant finding of this evidence assessment is not about the content of the reviewed studies but about their distribution. The volume of peer-reviewed research on SCI and supply chain risk management has grown substantially over the past decade, driven by the proliferation of big data and AI technologies in supply chain contexts and the disruption experiences of the COVID-19 pandemic. However, the geographic distribution of this research is heavily skewed toward developed economies, with a particular concentration on manufacturing contexts in North America, Western Europe, and East Asia.

The evidence base specific to Uganda is extremely thin. (Olwor, 2023) provides a broad analysis of Uganda's industrialisation challenges, including supply chain constraints, but does not examine SCI adoption or effectiveness. (Pius & Owin, 2024) offers the most directly relevant study, examining the challenges and opportunities of AI integration in Ugandan supply chain management, but the study is primarily conceptual and does not provide empirical evidence on SCI outcomes. (Tukamuhabwa et al., 2023) and (Alinda et al., 2023) provide empirical evidence on supply chain practices and institutional pressures in Ugandan manufacturing, but neither study addresses SCI specifically.

The implications of this evidence gap are significant. Policy recommendations and practitioner guidance on SCI adoption in Uganda currently rely on evidence from structurally different economies — economies with reliable infrastructure, deep supplier markets, accessible financial services, and institutional environments that support rather than constrain supply chain digitisation. The risk of misaligned interventions is high: SCI tools and strategies that are effective in a German or Japanese manufacturing context may fail in Uganda not because the tools are flawed but because the contextual conditions for their effectiveness are absent.

Evidence Hierarchy and Transferability Concerns Across Contexts is the evidence hierarchy for SCI in risk mitigation is dominated by correlational and simulation-based studies, with relatively few studies employing rigorous causal identification strategies. (Dou et al., 2024) and (Ivanov & Dolgui, 2020) provide rigorous mathematical and simulation-based frameworks that establish the theoretical conditions under which SCI improves risk outcomes, but these frameworks abstract away from the institutional and infrastructural specificities that determine real-world effectiveness. (Yang et al., 2021) and (Dubey et al., 2017) provide survey-based correlational evidence linking SCI-related constructs to supply chain performance, but the direction of causality is difficult to establish: firms with stronger supply chain performance may be more likely to invest in SCI, rather than SCI causing improved performance.

The transferability of developed-economy evidence to Uganda's context is questionable for several reasons. First, the institutional quality — the reliability of contract enforcement, the predictability of regulatory processes, and the availability of formal dispute resolution — that underpins supply chain digitisation in developed economies is substantially weaker in Uganda. Second, the infrastructure maturity that enables real-time data collection and transmission in developed-economy supply chains is absent in much of Uganda's manufacturing sector. Third, the supply chain formality — the extent to which transactions are documented, standardised, and conducted through formal channels — is lower in Uganda, reducing the data that SCI systems can draw on. (Okoye et al., 2024) provide a comparative review of risk management in international supply chains with case studies from both the United States and Africa, offering valuable insights into the contextual factors that differentiate risk management practice across these settings. However, their analysis, like most of the comparative literature, treats Africa as a single context, obscuring the substantial variation in supply chain conditions across African countries. The evidence base would benefit from country-specific studies that capture the institutional, infrastructural, and industrial specificities that shape SCI adoption and effectiveness in individual African manufacturing contexts.

(James et al., 2025) provide recent evidence from Zimbabwe's manufacturing SME sector that supply chain risk factors significantly affect firm performance and that technological capabilities moderate this relationship. While the Zimbabwean context shares some structural similarities with Uganda including infrastructural challenges, currency volatility, and a large SME sector the differences in political context, trade relationships, and industrial structure caution against direct extrapolation. The need for Uganda-specific empirical research is not a matter of academic completeness but of practical necessity: without it, Ugandan manufacturers and policymakers are navigating a complex adoption decision with a map drawn from a different territory.

REFERENCES

Adelhardt, N., & Berneiser, J. (2024). Risk analysis for agrivoltaic projects in rural farming communities in SSA. *Applied Energy*. https://doi.org/10.1016/j.apenergy.2024.122933.

Alinda, K., Tumwine, S., Nalukenge, I., Kaawaase, T. K., Sserwanga, A., & Navrud, S. (2023). Institutional pressures and sustainability practices of manufacturing firms in Uganda. *Sustainable Development.* https://doi.org/10.1002/sd.2704.

Amir Hossein Ordibazar e'tal (2024). Artificial intelligence applications for supply chain risk management considering interconnectivity, external events exposures and transparency: a systematic literature review

Anas Iftikhar et al., (2022). Digital Innovation, Data Analytics, and Supply Chain Resiliency: A Bibliometric-based Systematic Literature Review

Ankush Reddy Sugureddy (2024). PROACTIVE DATA GOVERNANCE: USING AI AND ML TO ANTICIPATE AND MITIGATE RISKS

Asamoah, D., Agyei-Owusu, B., & Ashun, E. (2020). Social network relationship, supply chain resilience and customer-oriented performance of small and medium enterprises in a developing economy. Benchmarking: *An International Journal. https://doi.org/10.1108/bij-08-2019-0374.*

Atoapem Frimpong Barimah (2024). Determinants of Supplier Risk Mitigation and Control in the Procurement of Goods and Services: A Review of Literature

Attia Hussien Gomaa (2026). Supply Chain Risk Management for Sustainable and Resilient Operations: A Comprehensive Review and Strategic Framework in the Era of Industry

Brintrup, A., Pak, J., Ratiney, D., Pearce, T., Wichmann, P., Woodall, P., & McFarlane, D. (2019). Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing. *International Journal of Production Research.* https://doi.org/10.1080/00207543.2019.1685705.

Chari, F., & Ngcamu, B. S. (2017). An assessment of the impact of disaster risks on dairy supply chain performance in Zimbabwe. *Cogent Engineering.* https://doi.org/10.1080/23311916.2017.1409389.

Chari, F., Ngcamu, B. S., & Novukela, C. (2020). Supply chain risks in humanitarian relief operations: a case of Cyclone Idai relief efforts in Zimbabwe. *Journal of Humanitarian Logistics and Supply Chain Management.* https://doi.org/10.1108/jhlscm-12-2019-0080.

Dou, R., Liu, X., Hou, Y., & Wei, Y. (2024). Mitigating closed-loop supply chain risk through assessment of production cost, disruption cost, and reliability. *International Journal of Production Economics.* https://doi.org/10.1016/j.ijpe.2024.109174.

Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Blome, C., & Luo, Z. (2019). Antecedents of Resilient Supply Chains: An Empirical Study. *IEEE Transactions on Engineering Management.* https://doi.org/10.1109/tem.2017.2723042.

Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Luo, Z., & Roubaud, D. (2017). Upstream supply chain visibility and complexity effect on focal company's sustainable performance: Indian manufacturers' perspective. *Annals of Operations Research.* https://doi.org/10.1007/s10479-017-2544-x.

Dmitry Ivanov (2026). Agentic digital twins: bridging model-based and AI-driven decision-making support for a new era of supply chain and operations management

Durán, C., Fernandez-Campusano, C., Carrasco, R., & Carrillo, E. (2024). DMLBC: Dependable machine learning for seaports using blockchain technology. *Journal of King Saud University - Computer and Information Sciences.* https://doi.org/10.1016/j.jksuci.2024.101918.

Dengyuhui Li (2023). Supply chain resilience from the maritime transportation perspective: A bibliometric analysis and research directions .

Fosso Wamba et al., (2024). Big Data Analytics-enabled Sensing Capability and Organizational Outcomes: Assessing the Mediating Effects of Business Analytics Culture.

Golan, M. S., Jernegan, L. H., & Linkov, I. (2020). Trends and applications of resilience analytics in supply chain modeling: systematic literature review in the context of the COVID-19 pandemic. *Environment Systems & Decisions*. https://doi.org/10.1007/s10669-020-09777-w.

Hossain, Md. I., Talapatra, S., Saha, P., & Belal, H. M. (2024). From Theory to Practice: Leveraging Digital Twin Technologies and Supply Chain Disruption Mitigation Strategies for Enhanced Supply Chain Resilience with Strategic Fit in Focus. G*lobal Journal of Flexible Systems Management.* https://doi.org/10.1007/s40171-024-00424-w.

Iyadunni Adewola Olaleye et al., (2024). Transforming supply chain resilience: Frameworks and advancements in predictive analytics and data-driven strategies

Ivanov, D., & Dolgui, A. (2020). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control.* https://doi.org/10.1080/09537287.2020.1768450.

Ilya Jackson et al., (2024). Generative artificial intelligence in supply chain and operations management: a capability-based framework for analysis and implementation.

Jack B. Reida et al., (2022). The Environment-Vulnerability-Decision-Technology Framework: A Process for Developing Multi-Disciplinary Decision Support Systems for Sustainable Development Applications

James, K., Tinashe, M., & Manyanga, W. (2025). Supply Chain Risk Factors, Technological Capabilities, and Firm Performance of Small to Medium Enterprises (SMEs). *Journal of Small Business Strategy.* https://doi.org/10.53703/001c.125910.

Jeyasheeli, P. G., Mahalakshmi, S. D., Sivagami, S. V., & Malarvizhi, N. (2026). Optimizing predictive analytics: a comparative study of deep learning approaches in big data mining for supply chain risk mitigation. *Journal of the Chinese Institute of Engineers.* https://doi.org/10.1080/02533839.2026.2659720.

Kumar, A. et al., (2023). Supply chain resilience in developing countries: a bibliometric analysis and future research directions

Lawrence, S. A., & Mupa, M. N. (2024). Innovative approaches to enhancing logistics for adapting to the evolving demands of manufacturing companies in East Africa through improved lean strategies. *World Journal of Advanced Research and Reviews*. https://doi.org/10.30574/wjarr.2024.23.3.2840.

Lugada, E., Komakech, H., Ochola, I., Mwebaze, S., Oteba, M. O., & Ladwar, D. O. (2022). Health supply chain system in Uganda: current issues, structure, performance, and implications for systems strengthening. *Journal of Pharmaceutical Policy and Practice.* https://doi.org/10.1186/s40545-022-00412-4.

Lutfor Rahman et al., (2026). AI-Driven Predictive Analytics for Supply Chain Resilience, Financial Risk Management, and Digital Marketing Strategy: A Unified Business Intelligence Framework.

Mutekwe et al., (2020).Supply chain risk management and operational performance in the food retail industry in Zimbabwe

Ngum, N., Mashingia, J., Ndomondo-Sigonda, M., Walker, S., & Salek, S. (2022). Evaluation of the Effectiveness and Efficiency of the East African Community Joint Assessment Procedure by Member Countries: The Way Forward. *Frontiers in Pharmacology.* https://doi.org/10.3389/fphar.2022.891506.

Ngboawaji Daniel Nte (2026). Intelligence and Global Transportation Supply Chain Management: The Case of Oil and Gas Supply in the Gulf of Guinea

Ojochenem., I et al., (2026). Effect of Supply Chain Risk Management on Organizational Performance of Nigeria Liquefied Natural Gas Limited (NLNG)

Okoye, C. C., Ofodile, O. C., Tula, S. T., Nifise, A. O. A., Falaiye, T., Ejairu, E., & Addy, W. A. (2024). Risk management in international supply chains: A review with USA and African Cases. *Magna Scientia Advanced Research and Reviews.* https://doi.org/10.30574/msarr.2024.10.1.0024.

Olwor, N. (2023). Industrialization of Economies with Low Level of Manufacturing Base: Case Study of Uganda. *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.4323103.

Pius, N., & Owin, O. L. O. (2024). Integration of Artificial Intelligence in supply chain management: challenges and opportunities in Uganda. *World Journal of Advanced Engineering Technology and Sciences.* https://doi.org/10.30574/wjaets.2024.12.2.0253.

Queiroz, M. M., Wamba, S. F., & Branski, R. M. (2021). Supply chain resilience during the COVID-19: empirical evidence from an emerging economy. *Benchmarking: An International Journal.* https://doi.org/10.1108/bij-08-2021-0454.

Raisul Islam Khan1et al., (2025). Multimodal Machine Learning for Proactive Supply Chain Risk Management: An AI-Driven Framework Integrating Sensor, Operational, and External Intelligence

R., K. S., Azadegan, A., & Ojha, D. (2023). A path to build supply chain cyber-resilience through absorptive capacity and visibility: Two empirical studies. Industrial Marketing Management. https://doi.org/10.1016/j.indmarman.2023.04.001.

Saidi, D., Alami, J. E., & Hlyal, M. (2021). Building Sustainable Resilient Supply Chains in Emerging Economies: Review of Motivations and Holistic Framework. IOP Conference Series: Earth and Environmental Science. https://doi.org/10.1088/1755-1315/690/1/012057.

Samir Ali Syed (2025). Digital Transformation in Procurement and Supply Chain Management: Leveraging AI, IoT, and Data Analytics for Operational Resilience.

Schäfer, S. F., Gorke, N. T., Cevirgen, C., Park, Y.-B., & Nyhuis, P. (2022). Elemente der „Fabrik der Zukunft“. Zeitschrift für wirtschaftlichen Fabrikbetrieb. https://doi.org/10.1515/zwf-2022-1029.

Seyed Ashkan Hosseini Shekarabi et'al (2025). Supply Chain Resilience: A Critical Review of Risk Mitigation, Robust Optimisation, and Technological Solutions and Future Research Directions

Shirin Shahsavary, et al., (2026). Risk Prediction in Design of Distributed Supply Chains Using Machine-Learning: A Bi-Objective Optimal Approach

Susitha, E., et al., (2024)Supply chain competitiveness through agility and digital technology: A bibliometric analysis.

Sureshkumar N. Narayanan, P.P., et al., (2024). Artificial Intelligence-Powered Risk Assessment in Supply Chain Safety

Stavros Kalogiannidis eta'l (2024). The Role of Artificial Intelligence Technology in Predictive Risk Assessment for Business Continuity: A Case Study of Greece

Paul Souma Kanti, et al. (2022). Artificial intelligence adoption in supply chain risk management: Scale development and validation

Rasha Aljaafreh (2026). Integrating Machine Learning and Business Intelligence into Supply Chain Risk Management for a Comprehensive Cybersecurity Framework: A Systematic Literature Review”

Shireen Al-Hourani (2025). A Systematic Review of Artificial Intelligence (AI) and Machine Learning (ML) in Pharmaceutical Supply Chain (PSC) Resilience: Current Trends and Future Directions.

Ssennoga, F., Mugurusi, G., & Oluka, P. N. (2019). Food insecurity as a supply chain problem. Evidence and lessons from the production and supply of bananas in Uganda. Scientific African. https://doi.org/10.1016/j.sciaf.2019.e00076.

Shiqi Qu, Xiangjiang Li, et'al (2025). Smart supply chain management: a systematic literature review and future research agenda.

Tiwari, S., Wee, H. M., & Daryanto, Y. (2018). Big data analytics in supply chain management between 2010 and 2016: Insights to industries. Computers & Industrial Engineering. https://doi.org/10.1016/j.cie.2017.11.017.

Tukamuhabwa, B. R., Mutebi, H., & Ojok, B. A. (2023). Supply Chain Performance in the Wooden Furniture Industry: The Effect of Institutional Pressures and Supply Chain Integration in a Developing Country Context. *Journal of African Business*. https://doi.org/10.1080/15228916.2023.2215572.

Yang, J., Xie, H., Yu, G., & Liu, M. (2021). Achieving a just–in–time supply chain: The role of supply chain intelligence. *International Journal of Production Economics.* https://doi.org/10.1016/j.ijpe.2020.107878.