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REVIEW

A Systematic Review on Applications of Deep Learning in Supply Chain Risk Management

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Abstract

The increasing complexity and globalization of modern supply chains have amplified exposure to multi-faceted risks, ranging from operational disruptions to systemic failures. Traditional risk management strategies, which are often based on static models, heuristic approaches, expert judgment, and limited real-time data, have struggled to offer the agility and foresight required in today's volatile environments. In recent years, deep learning (DL), a subfield of artificial intelligence (AI), has emerged as a transformative tool for supply chain risk management (SCRM), enabling data-driven, adaptive, and scalable solutions across the entire risk management lifecycle. Guided by four research questions addressing risk classification, architectural alignment, lifecycle effectiveness, and adoption barriers, this review synthesizes the recent literature on the application of DL techniques to four key stages of SCRM: risk identification, assessment, mitigation, and monitoring. By analyzing empirical studies, model architectures, and real-world applications, the paper highlights how DL enables predictive insights, real-time disruption detection, and proactive decision-making. A dynamic risk classification framework is introduced to better capture the evolving nature of supply chain threats. The review concludes by identifying critical challenges and future research directions, emphasizing the potential of DL to redefine resilience and strategic agility in supply chains.

Keywords Supply chain risk management · Risk classification · Deep learning · Reinforcement learning

1 Introduction

Supply chain risk management (SCRM) has gained increasing attention due to the growing complexity and interconnectedness of global supply chains (SC). As supply

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networks expand across multiple regions, they become more vulnerable to disruptions arising from natural disasters, pandemics, geopolitical tensions, supplier failures, and financial crises. Over the past few decades, major disruptions such as the 2000 Phillips semiconductor plant fire, the 2011 Japanese tsunami, and the 2011 Thailand floods have underscored the need for structured risk management frameworks to enhance SC resilience [1]. The growing reliance on lean manufacturing, just-in-time (JIT) inventory systems, and global outsourcing has further exacerbated these risks due to a limited amount of inventory buffer, necessitating robust strategies to anticipate and mitigate SC vulnerabilities [2].

Traditionally, SCRM relied on qualitative and quantitative approaches, emphasizing risk identification, assessment, mitigation, and monitoring. One of the widely recognized frameworks in early SCRM research was the risk management process (RMP), introduced by Tummala and Schoenherr (2011) [3]. Their framework provided a structured methodology for assessing risks based on expert judgment and probabilistic models. Another prevalent approach was failure mode and effects analysis (FMEA), which systematically evaluated potential failure points within supply chains, prioritizing risks based on their likelihood, severity, and detectability [4]. These traditional methods were supplemented by scenario planning and simulation models, where tools like Monte Carlo simulations and stochastic models were employed to estimate disruptions and their cascading effects [5]. Additionally, researchers explored network analysis and risk mapping techniques, which helped visualize and effectively communicate SC vulnerabilities and assess structural weaknesses [6].

Despite their widespread adoption, traditional SCRM techniques have several limitations. Most conventional models are static in nature, assuming that past trends can accurately predict future risks, which often leads to inflexible and outdated risk mitigation strategies. Furthermore, these methods are largely reactive, focusing on post-disruption assessments rather than real-time risk prediction. Since SC disruptions are dynamic and evolve rapidly, traditional methods often lack the agility to respond to real-time events. Another challenge is the limited integration of real-time data sources, as manual risk assessments and statistical simulations require extensive human intervention and cannot efficiently process vast amounts of supply chain data. Additionally, conventional models often struggle to capture the multi-tier dependencies inherent in modern global supply chains, where risks in one part of the network can quickly propagate across multiple stakeholders [7].

Recognizing these challenges, researchers and practitioners have increasingly turned to artificial intelligence (AI) and machine learning (ML) techniques to address the limitations of traditional SCRM. With the ability to analyze massive datasets, detect patterns, and generate predictive insights, deep learning (DL) has emerged as a transformative tool in modern risk management. Unlike conventional methods, DL-based models can continuously learn and adapt to new risk factors, making them well-suited for real-time risk monitoring and mitigation. This review systematically examines the role of DL in SCRM, providing an in-depth analysis of how various DL methodologies have been applied in different stages of SCRM. The remainder of this paper is structured as follows: Section 2 details the review methodology, including data sources, search strategies, and inclusion criteria. Section 3 discusses the existing risk classification frameworks, transitioning towards a more dynamic risk taxonomy.

Section 4 presents an overview of DL techniques, highlighting their capabilities and relevance to SCRM. Section 5 delves into the applications of DL across key SCRM stages and analyzes relevant literature for each stage. Section 6 highlights critical problems in SCRM where DL shows significant potential, followed by Sections 7 and 8, which provide a discussion of key findings, their implications, challenges, and future research directions.

2 Review Methodology

To systematically examine the role of DL in SCRM, this review employs a structured methodology designed to ensure comprehensive coverage and analytical rigor. Our approach is guided by four research questions (RQ) that address both theoretical understanding and practical applications of SCRM:

- **RQ1:** How can supply chain risks be classified in a way that reflects their dynamic, evolving nature in modern digitalized networks?
- **RQ2:** How do the architectural characteristics of different DL models align with the dynamic properties of supply chain risks?
- **RQ3:** Which DL architectures are most effective for addressing different stages of the SCRM life cycle?
- **RQ4:**What are the primary challenges limiting the widespread adoption of DL in SCRM?

These questions guide our systematic literature search, data extraction process, and analytical framework.

2.1 Data Sources and Search Strategy

Given the interdisciplinary nature of this topic, a structured review of the literature was conducted, based on [5], to ensure comprehensive coverage of studies that contribute to understanding how DL techniques improve supply chains. The literature search was performed using multiple academic databases to retrieve high-quality peer-reviewed journal articles, conference proceedings, and review papers. The primary databases included Google Scholar, IEEE Xplore, Elsevier (Science Direct), Springer, Taylor & Francis, JSTOR, Emerald Insight, Web of Science, and Scopus. These databases were chosen for their broad coverage of engineering and management disciplines, and their inclusion of high-impact peer-reviewed publications in the deep learning, operations research, and supply chain domains. To maximize the relevance of the retrieved articles, Boolean search operators (AND, OR) were applied in the construction of search queries. The primary search terms included the following:

- “Deep Learning” OR “Machine Learning” OR “Artificial Intelligence” AND “Supply Chain Risk”
- “Risk Identification” OR “Risk Assessment” OR “Risk Mitigation” OR “Risk Monitoring” AND “Supply Chain”

- "Reinforcement Learning" AND "Supply Chain Optimization"
- "Neural Networks" AND "Supply Chain Disruptions"

The rationale for this keyword selection lies in the need to capture the intersection of two core areas: advanced DL methods and practical risk-oriented applications within supply chains. In addition, incorporating risk-related keywords that cover different stages of the SCRM life cycle ensured that the literature was appropriately aligned with the scope of this review.

To complement the search, a snowball approach [8] was used, where reference lists of highly cited articles were examined to identify seminal works and other relevant contributions. This technique was essential for capturing foundational studies and emerging trends.

The selection process followed a multistage screening protocol (Fig. 1), filtering studies based on their relevance, methodological rigor, and contribution to the field. The structured nature of this process ensured that only technically grounded and topically aligned articles were included, resulting in a curated set of high-quality research. To maintain the rigor of the review, specific inclusion and exclusion criteria were established (Table 1). The rationale behind these criteria is grounded in the aim of maintaining academic and technical integrity while ensuring that the review remains focused on the specific intersection of DL and SCRM. Including only sources with clear methodological grounding filters out unverified or speculative content, while requiring explicit DL applications ensures that each included study offers relevant insight into how DL is utilized within the supply chain risk context. Excluding generic AI or ML applications avoids diluting the review's focus and keeps it centered on actionable, field-specific research.

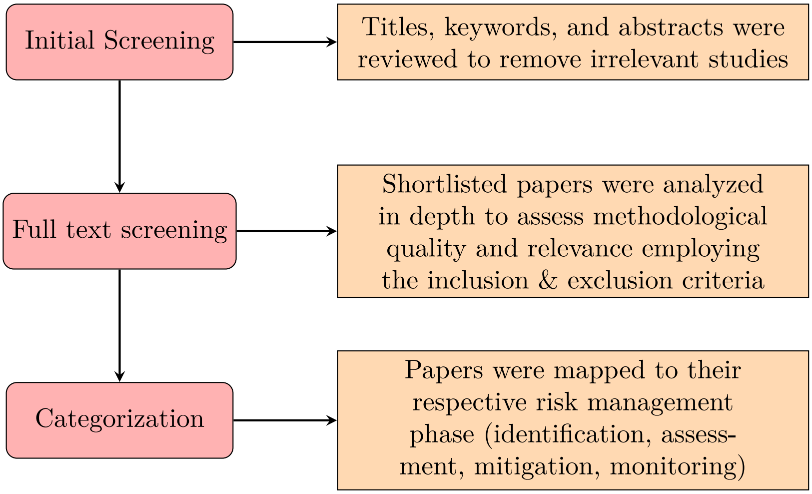

Fig. 1 Literature selection process

Table 1 Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
• Peer-reviewed journal articles, conference proceedings, and authoritative review papers	• Studies focused solely on traditional risk management techniques without integrating AI or DL methodologies
• Studies explicitly discussing DL applications in SCRM	• Papers discussing general AI models without specific applications in SCRM
• Papers covering any of the four key risk management phases—identification, assessment, mitigation, or monitoring	• Duplicate studies, non-peer-reviewed articles, or opinion-based reports lacking empirical validation
• Research providing empirical results, case studies, or comparative evaluations of DL techniques in SCRM	• Research with insufficient technical details on DL architectures used in SCRM

2.2 Citation Networks and Keyword Analysis

To deepen the thematic and chronological understanding of literature in this review, two types of bibliometric visualizations were employed: a citation network and a co-occurrence network. These were constructed using the curated set of references identified through the methodology outlined in Section 2.1.

The citation network (Fig. 2) illustrates the intellectual lineage of the field by mapping how key papers cite and influence one another. Each node represents a unique publication, with node size scaled by citation count, while edges denote citation relationships. Foundational works, such as those by Peck (2004) [9], Tang (2006) [10], and Christopher (2003) [11], appear on the left, indicating their early and influential role in shaping risk classification and mitigation frameworks. These studies heavily inform

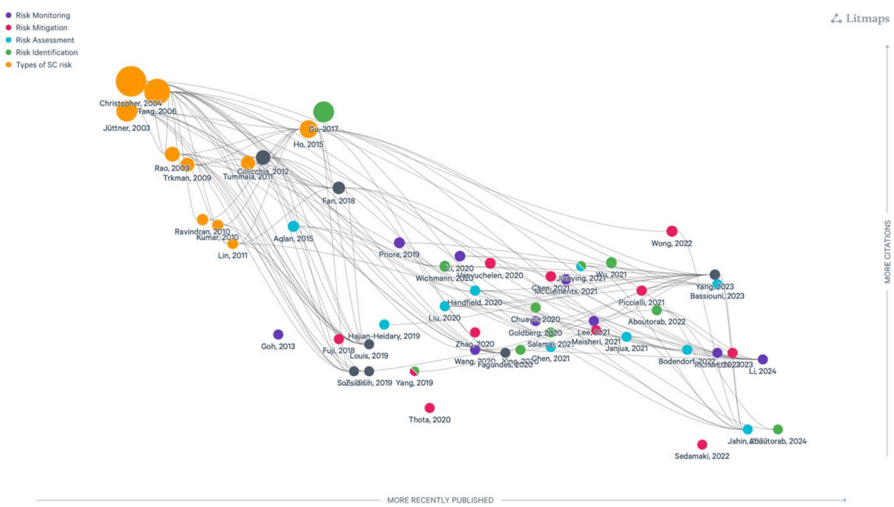

Fig. 2 Citation network

midstream contributions from Tummala and Schoenherr (2011) [3], Rao and Goldsby (2009) [4], and Baryannis et al. (2018) [12], which further operationalize supply chain risk typologies and modeling techniques. Toward the right end of the network, a visible shift is observed as more recent literature integrates artificial intelligence (AI) and deep learning (DL) methodologies. Works by Xiao (2023) [13], Dudek (2023) [14], and Ivanov (2021) [15] highlight this transition by focusing on automated disruption forecasting, resilience quantification, and data-driven decision support systems. The citation topology thus captures the disciplinary evolution of SCRM from rule-based and probabilistic approaches to more adaptive, learning-driven paradigms.

Complementing this, the co-occurrence network (Fig. 3) presents a thematic snapshot of the field by mapping how frequently key terms appear together in the titles and abstracts of the reviewed literature. Prominent clusters emerged around terms such as deep learning, supply chain risk, resilience, forecasting, disruption, and blockchain. These dense linkages reflect the consolidation of DL applications in core SCRM areas such as demand volatility prediction, inventory management, anomaly detection, and traceability. Additionally, terms like reinforcement learning, social media, sustainability, and ESG (environmental, social, and governance) form satellite clusters, indicating growing interest in socially-aware and real-time risk mitigation strategies. Notably, strong ties between keywords such as robustness, simulation, and optimization suggest a convergence of DL with simulation-optimization hybrids for scenario planning. Taken together, Figs. 2 and 3 offer a dual lens—one structural and one thematic—on how the academic discourse in DL-enabled SCRM has evolved and where it is currently converging.

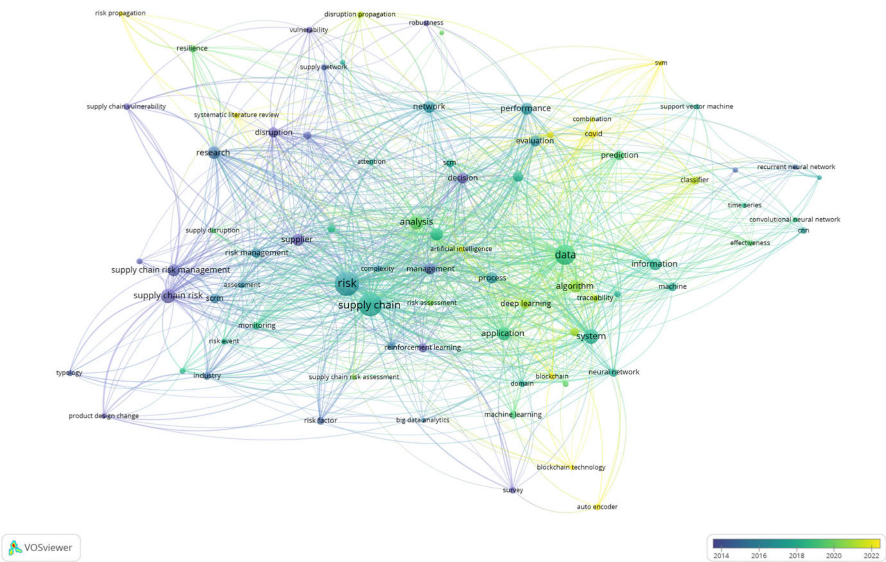

Fig. 3 Co-occurence matrix

3 Supply Chain Risk Classification

Before examining how DL architectures address supply chain risks, it is essential to understand how these risks have traditionally been classified and why existing frameworks require evolution (RQ1). Risk classification has long been a crucial part of SCRM, providing structured frameworks to understand and mitigate disruptions. As outlined by Baryannis et al. (2018) [12], two widely recognized classification methods are network-level risk classification and process-based risk classification, both of which offer valuable insights into how risks manifest within supply chains.

The network-level classification categorizes risks based on their position within the supply chain network. This approach distinguishes external risks (arising from macroeconomic, environmental, or geopolitical factors), network-level risks (affecting suppliers, logistics providers, and demand fluctuations), and firm-level risks (internal operations, production processes, and organizational inefficiencies). This hierarchical structure provides a multilayered perspective, helping organizations identify whether risks originate externally, within the supply chain partners, or from internal weaknesses.

Process-based classification, on the other hand, focuses on the risks that arise from specific functions of the supply chain. Risks are categorized into supply risks (supplier failures, raw material shortages), demand risks (market volatility, forecasting errors), operational risks (manufacturing inefficiencies, process disruptions), logistics risks (transportation failures, inventory imbalances), and control risks (compliance failures, cybersecurity threats). This classification is particularly useful for firms managing complex, multistage supply chains, as it aligns risks with specific business functions and operational decisions.

Although these frameworks have played a fundamental role in understanding supply chain risks (Table 2), they primarily rely on static classifications that do not account for real-time risk fluctuations or emerging disruptions such as cyber threats, AI-driven supply chain failures, or cascading disruptions across interconnected levels. Traditional taxonomies assume that risks fall into predefined categories, whereas modern supply chains demand more adaptive classification models.

3.1 Transitioning to a Dynamic Risk Classification Framework

While network-level and process-based classifications provide a structured foundation, they lack the ability to continuously update risk assessments based on evolving conditions [21]. Given the increasing complexity and interconnected nature of supply chain networks, a more adaptive approach to risk classification is necessary—one that reflects the dynamic nature of modern digitalized supply chains and enables systematic evaluation of technological interventions.

We propose a dynamic classification framework based on three fundamental dimensions: predictability (how risks emerge over time), controllability (the degree of organizational influence over risk factors), and propagation (how risks spread across supply networks) (Fig. 4). This three-dimensional taxonomy addresses RQ1 by providing a more adaptive alternative to static classifications, while simultaneously establishing an analytical lens for evaluating how different DL architectures align

Table 2 Traditional supply chain risk classification

Author	Risk classification
Juttner et al. (2003) [16]	• Environmental risks • Network-related risks • Organizational risks
Christopher and Peck (2004) [11]	• External to network: environmental risks • External to firm but internal to network: demand and supply risks • Internal to firm: process and control risks
Tang et al. (2006) [10]	• Operational risks: uncertain customer demand, supply and costs • Disruption risks: earthquakes, floods, hurricanes, terrorist, and economic crises
Trkman and McCormack (2009) [17]	• Endogenous risks: market and technology turbulence • Exogenous risks: discrete events (e.g., terrorist attacks, disease outbreaks, worker strikes) and continuous events (e.g., inflation rate, consumer price index changes)
Rao and Goldsby (2009) [4]	• Environmental factors: political, policy, macroeconomic, social • Industry factors: input market, product market, competition • Organizational factors: agency, credit, liability, operating • Problem-specific factors: risk interrelationship, objectives and constraints, task complexity • Decision-maker factors: knowledge/skill/biases, information seeking, rules and procedures, bounded rationality
Ravindran et al. (2010) [18]	• Value-at-risk (VaR): labor strike, terrorist attack, natural disaster • Miss-the-target (MtT): late delivery, missing quality requirements
Kumar et al. (2010) [19]	• Internal operational risks: demand, production and distribution, supply risks • External operational risks: terrorist attacks, natural disasters, exchange rate fluctuations
Tummala and Schoenherr (2011) [3]	• Demand, delay, disruption • Inventory, manufacturing (process) breakdown, physical plant (capacity), supply (procurement) • System, sovereign, and transportation risks
Lin and Zhou (2011) [20]	• Risk in the external environment • Risk within the supply chain • Internal risk

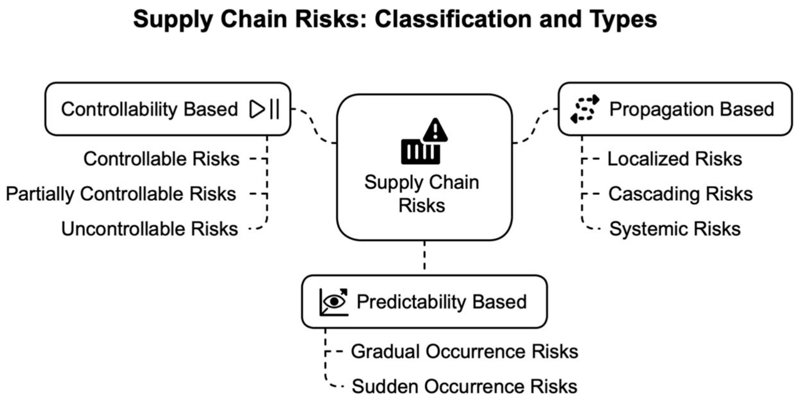

Fig. 4 Dynamic risk classification framework

with specific risk characteristics (RQ2, RQ3). The framework's utility for architectural selection will become evident through the systematic analysis presented in Section 5.

1. **Predictability-based risk classification:** Some risks emerge gradually over time, while others occur suddenly and unpredictably. Classifying risks based on predictability allows organizations to adopt proactive versus reactive strategies [10, 22, 23].
    - **Gradual occurrence risks:** These risks evolve over time and can often be forecasted using historical data and trend analysis. Examples include market fluctuations, supplier financial instability, and regulatory changes. Traditional statistical models and machine learning techniques, such as time-series forecasting, are commonly used to predict these risks.
    - **Sudden occurrence risks:** These risks arise unexpectedly, often due to catastrophic disruptions such as natural disasters, pandemics, cyberattacks, or geopolitical crises. Such risks require real-time anomaly detection using DL models, which can identify rare but high-impact events before they escalate.
2. **Controllability-based risk classification:** Risk exposure varies based on how much control an organization has over the underlying cause of the disruption. Risks can be classified as controllable, partially controllable, or uncontrollable based on their degree of influence within the supply chain [3, 9, 16].
    - **Controllable risks:** These risks are internally driven and can be mitigated through strategic decisions and process improvements. Examples include inventory shortages, process inefficiencies, and workforce management issues. Machine learning algorithms and optimization models are increasingly used to automate risk mitigation for these categories.
    - **Partially controllable risks:** These risks are external but manageable through collaborative strategies and contractual safeguards. For instance, supplier failures, demand volatility, and logistics disruptions fall into this category. AI-driven risk assessment tools enable organizations to monitor and predict

these risks by analyzing supplier performance, transportation data, and customer behavior.
- **Uncontrollable risks:** These risks originate from macro-environmental factors and are largely beyond direct organizational control. Examples include geopolitical instability, extreme weather events, and financial market collapses. While these risks cannot be prevented, DL models can identify potential markers or indicators and enhance preparedness by generating scenario-based risk simulations and adaptive response strategies.

3. **Propagation-based risk classification:** Risks also differ in their ability to spread across the supply chain, affecting multiple stakeholders and tiers. Understanding how risks propagate allows firms to prioritize intervention efforts more effectively [11, 24–26].

   - **Localized risks:** These risks remain contained within a single organization or supply chain node. Examples include a production line failure at a specific plant or a delayed shipment from a particular supplier. These can often be addressed using real-time monitoring and automated alerts.
   - **Cascading risks:** These risks spread across multiple supply chain tiers, amplifying their impact. A supplier's bankruptcy, for instance, may disrupt downstream operations, causing shortages across multiple firms. AI-powered network analysis can model risk propagation pathways and identify critical dependencies that require proactive mitigation.
   - **Systemic risks:** These risks affect the entire supply chain ecosystem, leading to widespread disruptions across industries. Examples include the global semiconductor shortage, pandemic-driven supply chain collapses, and major cyberattacks on logistics infrastructure. Systemic risks require global risk intelligence systems, leveraging DL for predictive risk assessment and automated contingency planning.

4 Deep Learning: A General Overview

Having established a dynamic framework for understanding supply chain risks, we now turn to the technological capabilities that enable more effective risk management. Deep learning (DL), a specialized branch of artificial intelligence (AI), has emerged as a transformative enabler for SCRM, offering capabilities uniquely suited to the challenges identified in our risk classification framework.

Supply chain risk management (SCRM) has traditionally relied on statistical models, heuristic approaches, and expert-driven assessments to mitigate potential disruptions. However, the increasing complexity of global supply chains—characterized by multi-tiered supplier relationships, geographically dispersed networks, and volatile geopolitical and market conditions—has exposed the limitations of static and human-centric approaches [27]. Simultaneously, the proliferation of digitized supply chain operations has led to the generation of massive volumes of structured and unstructured data across the value chain. These shifts have necessitated a transition toward risk management systems that are automated, scalable, adaptive, and capable of learning from high-velocity data streams [28]. In this context, DL has emerged as a powerful enabler, offering enhanced capabilities in non-linear predictive modeling, real-time anomaly detection, and self-optimizing decision-making systems.

The fundamental strength of DL lies in its ability to process large-scale, high-dimensional, and heterogeneous datasets—a characteristic that maps directly to the fragmented and multi-modal nature of supply chain data [29]. These datasets span across structured formats such as transaction logs, inventory levels, supplier evaluations, and IoT sensor outputs, as well as unstructured sources like contractual documents, supplier audits, regulatory filings, and external news or social media feeds. The DL models excel in environments where relationships among variables are not explicitly defined but need to be inferred from data distributions, making them particularly well-suited for risk scenarios involving hidden dependencies, latent signals, or rare events. Furthermore, DL's ability to scale across time and geography allows for end-to-end modeling of risks that originate in one region or supplier and cascade through interconnected nodes of the supply chain [30].

Unlike traditional machine learning (ML) techniques, which require manual feature engineering and often struggle to generalize beyond the training distribution, DL architectures automatically learn hierarchical feature representations. This allows models to extract relevant patterns from raw data at various levels of abstraction, from low-level signals (e.g., transaction frequency anomalies) to high-level concepts (e.g., potential supplier default risk or market stress indicators) [31]. These capabilities enable DL models to build generalizable internal representations that not only improve accuracy but also allow rapid adaptation to evolving risk profiles, such as sudden demand surges, transportation bottlenecks, or supplier insolvency due to unforeseen externalities. In contrast to static models, DL systems can continuously update their internal parameters as new data becomes available, resulting in risk assessment frameworks that are context-aware, data-driven, and resilient to change. This adaptability is particularly crucial in SCRM, where disruptions rarely follow deterministic patterns and are often triggered by complex interactions among economic, political, operational, and environmental factors.

4.1 Evolution of DL in SCRM

Historically, supply chain risk assessment has been grounded in deterministic and probabilistic models such as Monte Carlo simulations for assessing disruption probabilities [32, 33], Bayesian networks for modeling risk dependencies [34, 35], and regression-based demand forecasting [36, 37]. Additionally, decision trees and rule-based expert systems have played a central role in evaluating supplier performance, quantifying lead time variability, and identifying early warning indicators based on predefined decision logic [38–40]. While effective in structured environments, these models are often limited in their ability to integrate diverse data sources, adapt to changing contexts, or model non-linear interactions that characterize modern supply chains.

The emergence of traditional ML techniques, such as support vector machines, logistic regression, and ensemble models, marked a shift toward data-driven risk modeling. These methods enhanced the ability to identify patterns in historical data and classify events such as supplier failure or shipment delays. However, they remained constrained by the need for extensive manual preprocessing and feature engineering, and they typically performed poorly in non-stationary environments—a common challenge in globalized supply chains exposed to regulatory shifts, raw material price fluctuations, and demand-side shocks.

Deep learning provides a solution to these limitations by enabling models to learn complex, multilayered abstractions from raw data, capturing both local and global dependencies. Through architectures such as deep feedforward networks, convolutional layers, and memory-based recurrent units, DL systems can model temporal trends, spatial correlations, and relational hierarchies without the need for explicit feature design [31]. Neural networks can ingest diverse datasets, including financial transactions, supplier evaluations, and logistics performance metrics, allowing for real-time learning and risk classification. Furthermore, the use of continuous learning mechanisms allows these models to remain responsive to emerging trends and real-time risk signals, improving forecasting accuracy and decision lead time. These advancements have made DL increasingly central to data-driven SCRM strategies, superseding rule-based heuristics with proactive, learning-based systems capable of generalizing across uncertainty and scale.

4.2 Major DL Architectures Used in SCRM

Several DL architectures have been applied to different phases of SCRM, enhancing capabilities in risk identification, assessment, mitigation, and monitoring. These architectures vary in terms of learning mechanisms, data compatibility, and practical utility, allowing them to address diverse use cases across the SCRM landscape.

Artificial neural networks (ANNs) [41] have been extensively used for supplier risk assessment, fraud detection, and anomaly identification [42, 43]. Their multilayered architecture enables the modeling of complex, high-dimensional relationships across variables such as supplier financial records, transactional logs, and regulatory compliance scores. ANNs excel in supervised learning environments where labeled historical data is available. They have demonstrated improved classification performance over traditional logistic regression and decision tree approaches in risk profiling tasks. However, ANNs are sensitive to hyperparameter tuning and may overfit in low-sample scenarios common in rare-event risk modeling. Recent studies [44] have addressed this limitation by combining ANNs with regularization techniques or ensemble methods to improve robustness and interpretability in risk evaluations.

Convolutional neural networks (CNNs), originally developed for image processing, have been adapted for text analytics and risk signal extraction [45–47]. These architectures apply convolutional filters to capture local patterns in input data, making them effective in analyzing regulatory reports, supplier contracts, and market news for early signs of disruption. For text, 1-D CNNs can identify phrase-level risk indicators, while for visual inspection tasks, 2-D CNNs help detect defective products and quality inconsistencies within manufacturing or logistics chains. The weight-sharing property of CNNs allows efficient learning from smaller datasets, but their limited temporal awareness makes them less suitable for modeling long-term sequential dependencies, requiring hybrid architectures when applied to time-evolving risk profiles.

Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have been proven valuable in time-series forecasting and sequential risk assessment [48–50]. These models are designed to retain memory of prior inputs, making them ideal for capturing temporal dependencies in demand patterns, logistics disruptions, and supplier performance over time. While traditional RNNs often struggle with vanishing gradients, LSTMs incorporate gating mechanisms to preserve long-term information, enabling them to detect lagged effects or recurring disruptions across the supply chain. Applications include dynamic lead time forecasting, inventory volatility tracking, and modeling cascading effects of upstream failures. Their ability to model multivariate sequences also allows the integration of external variables, such as fuel prices, weather conditions, or geopolitical indicators, into supply chain risk predictions.

Autoencoders have been widely employed for unsupervised anomaly detection in SCRM, particularly in settings where labeled data is scarce or unavailable [51–53]. These models operate by compressing input data into a latent representation and reconstructing it, with the reconstruction error serving as a proxy for abnormality. In supply chain contexts, this approach is used to detect fraudulent transactions, operational irregularities, and sudden deviations in supplier behavior or shipping performance. Autoencoders are well-suited for high-dimensional datasets, and their compact latent spaces can be further leveraged for clustering and visualization of risk patterns. However, tuning the reconstruction error threshold for anomaly classification requires careful calibration, often in consultation with domain experts or through integration with downstream supervised models.

Reinforcement learning (RL) has gained traction in dynamic risk mitigation and decision-making tasks related to supply chain resilience planning [54–56]. RL frameworks train agents to interact with simulated supply chain environments and learn optimal policies through reward feedback mechanisms. Unlike traditional optimization models, which rely on fixed rules, RL can adapt to changing conditions and learn from trial-and-error interactions. In SCRM, RL has been applied to inventory control under uncertainty, real-time route adaptation during disruptions, and supplier diversification strategies. Multi-agent RL models extend this framework to enable coordination among multiple supply chain stakeholders, such as manufacturers, distributors, and logistics providers. These models have been employed in disaster recovery simulations, where agents learn to reroute shipments, allocate scarce resources, and restore network connectivity. However, RL's reliance on extensive simulation data and its black-box decision process poses challenges for real-world deployment, especially in high-stakes risk scenarios requiring interpretability and policy validation.

Together, these architectures form the foundation for the emerging field of deep learning-driven supply chain risk management. Each architecture brings distinct strengths suited to specific data types and risk challenges, and many real-world applications now employ hybrid models that combine their complementary capabilities.

In the following section, we explore how these architectures are leveraged across the four major phases of the SCRM lifecycle—risk identification, risk assessment, risk mitigation, and risk monitoring. Beyond this process-oriented organization, our cross-cutting analysis (Section 5.5) will reveal systematic patterns on how architectural properties align with the dynamic risk dimensions introduced in Section 3.1.

5 Applications of Deep Learning in SCRM

Building on the foundational capabilities of DL discussed in earlier sections, its value becomes even more apparent when mapped onto the structured, process-oriented nature of SCRM. This section directly addresses RQ3 (which DL architectures are most effective for different SCRM stages) while building evidence for RQ2 (how architectural characteristics align with dynamic risk properties).

The literature commonly organizes SCRM into four interlinked stages: risk identification, risk assessment, risk mitigation, and risk monitoring—a framework that reflects both the logical sequence of managing uncertainty and the evolving nature of risk across a supply chain lifecycle. This phased model has been widely adopted in academic and practitioner literature [1–3, 87] and offers a useful scaffold for analyzing where and how DL methods are applied most effectively.

Each stage of this risk lifecycle presents distinct analytical demands. Risk identification often involves processing unstructured data to detect early warning signals; risk assessment requires learning complex relationships between variables to estimate impact and likelihood; mitigation depends on adaptive decision-making under uncertainty; and monitoring calls for real-time tracking and anomaly detection across diverse data streams. DL's versatility across data types and learning paradigms makes it particularly well-suited for contributing to each of these domains in targeted and complementary ways. As highlighted in [12, 13], and [88], DL has already shown impact in tasks such as supplier risk classification, disruption forecasting, and real-time logistics tracking, underscoring its applicability across the full SCRM spectrum. A consolidated taxonomy of DL architectures and their corresponding applications in SCRM is presented in Table 3, summarizing and organizing references that are examined in greater detail in the subsections that follow. This section addresses RQ3 by systematically examining how specific DL architectures have been utilized across the four SCRM stages. The applications reviewed here reveal patterns in architecture-risk alignment that will be explicitly synthesized.

In the subsections that follow, we examine how specific DL architectures have been utilized within each of the four SCRM stages. By organizing this review around the risk management process, we aim to provide a structured understanding of DL's diverse contributions and offer insights into how different models align with the unique demands of each phase.

5.1 Risk Identification

Risk identification serves as the foundational step in SCRM, focusing on the early detection of potential threats that could destabilize supply chain operations. With the increasing complexity and digitization of global supply chains, DL techniques have emerged as powerful tools for uncovering hidden patterns, identifying vulnerabilities, and enhancing traceability across diverse data sources.

A growing body of literature has shown that DL methods are particularly well-suited to process heterogeneous, high-dimensional data such as textual records, sensor streams, financial indicators, and social media signals. One approach applied text mining methods—including word sense induction and TF-IDF (Term Frequency-

Table 3 DL architectures and their applications in SCRM

DL algorithm	Application in SCRM	References
Artificial neural networks	• Supplier risk assessment • Fraud detection • Anomaly detection	[57–60]
Convolutional neural networks	• Analyzing regulatory reports, supplier contracts, market news • Quality control using image recognition	[61, 62]
Recurrent neural networks/ LSTM/GRU/TCN	• Predict demand volatility • Assess supplier performance over time • Identify anomalies in logistics and inventory flows	[63–65]
Autoencoders	• Identify fraudulent transactions and unexpected deviations in performance • Flag suspicious supplier behaviors, inconsistent shipping patterns, cybersecurity threats	[66, 67]
Reinforcement learning (RL/DRL/MARL)	• Learn optimal risk mitigation strategies over time • Evaluate supplier performance and adapt procurement decisions	[68–74]
Hybrid/other (GANs, fuzzy, simulation, NLP-based)	• Fuzzy logic integrated with neural networks for preemptive risk scoring and supplier evaluation • GAN-enhanced frameworks for generating synthetic disruption scenarios and improving resilience under uncertainty • Simulation-optimization approaches combined with DL for robust sourcing and workflow design • NLP pipelines for extracting disruption signals from unstructured news and social media data	[14, 67, 75–86]

Inverse Document Frequency) weighting—on unstructured financial documents to identify key risk indicators in supply chain financing, such as insufficient cash flow oversight and poor partner collaboration [77]. Another method leveraged deep neural networks to extract and visualize supply chain entities and relationships from news data, facilitating early detection of geopolitical and reputational risks [78].

DL methods have also been integrated with optimized classification models for detecting operational risks. A dynamic voting classifier enhanced by a Sine Cosine Dynamic Group (SCDG) optimization technique [79] is used to detect internal and external risks in digitally integrated supply chains. The approach demonstrated robust accuracy when applied to transactional and logistics data. Along similar lines, a back propagation neural network (BPNN) model was employed to assess risks in sustainable supply chains, revealing vulnerabilities associated with supplier dependability, shifts in market demand, and quality inconsistency in agricultural logistics [59].

Beyond classification-based approaches, recent work has explored disruption detection using temporal and streaming operational data, where deviations from normal system behavior may signal emerging risks. Ashraf et al. [89] developed a hybrid deep learning framework within a cognitive digital supply chain twin that combines deep autoencoders with one-class support vector machines for anomaly detection. The model learns representations of normal operational patterns from multivariate time-series data and flags abnormal system states through reconstruction errors and boundary-based detection, enabling the identification of disruptions prior to observable degradation in supply chain performance.

Complementary to signal-based detection, network- and structure-aware DL methods have been applied to uncover latent vulnerabilities embedded within supply chain topologies. Tan et al. [90] proposed a direction-sensitive graph learning model that captures asymmetric dependency relationships among firms to detect financial risk propagation. Their formulation emphasizes how exposure accumulates and transmits across directed supply chain links, providing a structural view of risk identification that extends beyond isolated firm-level indicators.

In certain domains, DL models have enabled traceability and behavioral monitoring to combat illegal practices and environmental risks. Convolutional neural networks (CNNs) have been used to analyze GPS trajectories of fishing vessels, enhancing traceability in maritime supply chains and contributing to efforts against illegal, unreported, and unregulated fishing [61]. Social media and open-source intelligence have also become pivotal in identifying market and demand-related risks. For example, one model utilized a multi-source DL architecture to forecast fluctuations in the US oil market during the COVID-19 pandemic using Twitter data, highlighting the potential of sentiment-driven risk identification during large-scale disruptions [80].

RL methods have been employed to improve disruption discovery by simulating environment-agent interactions and adapting inspection policies over time [68]. This dynamic approach enables systems to uncover less obvious or previously unseen disruptions. They further enhanced this approach by integrating natural language processing (NLP) with RL [69]. Their model, RL-SCRI (Reinforcement Learning for Supply Chain disruption Risk event Identification), was able to extract relevant disruptions from a vast corpus of news articles and reports, outperforming benchmark models in identifying both direct and indirect risk events across global supply chains. Additionally, attention has been drawn to threats targeting the ML models themselves. One line of research identified backdoor attacks, known as "BadNets," which can compromise pre-trained models and pose serious vulnerabilities in the ML-driven supply chain risk identification pipeline [91].

Together, these studies showcase the multi-faceted role of DL in modern risk identification: from analyzing unstructured texts and behavioral data to simulating disruptions and defending the supply chain itself. As supply chains continue to digitize and decentralize, DL-enabled risk identification will become increasingly indispensable in achieving resilience and proactive risk management.

5.2 Risk Assessment

Once potential disruptions have been identified, the next critical step in the SCRM lifecycle is risk assessment—evaluating the likelihood, impact, and propagation potential of those risks. This phase is increasingly being enhanced by DL which offers improved precision, scalability, and adaptability across complex and uncertain supply chain environments.

A prominent approach in DL-based risk assessment involves learning temporal patterns and nonlinear dependencies within supply chain data. One study utilized long short-term memory (LSTM) networks to evaluate oil import risks for China by accounting for dimensions such as accessibility, affordability, and resilience [63]. Their model effectively captured time-series trends to forecast evolving risks and offered greater granularity than conventional forecasting methods. In a similar direction, another work applied a suite of recurrent architectures—including BiLSTM (bidirectional LSTM), GRU (gated recurrent unit), and TCN (temporal convolutional networks)—to predict disruptions during the COVID-19 pandemic, illustrating how deep sequential models can adapt to volatile environments by learning delay patterns and their cascading effects across logistics networks [64].

Beyond continuous forecasting, recent studies have explored DL-based frameworks that explicitly evaluate discrete risk levels by integrating heterogeneous operational signals. Chen and Zhang [92] proposed a two-stage deep learning model for supply chain risk evaluation that combines data augmentation with spatiotemporal feature learning to address class imbalance in risk categories. Their framework produces multi-level risk assessments (e.g., low, moderate, high) from multi-source data streams, supporting severity-aware prioritization rather than binary disruption prediction.

While these temporal models enable robust forecasting, other studies have focused on credit and financial risk evaluation using both DL and hybrid frameworks. One example employed an optimized backpropagation neural network (BPNN) integrated with genetic and particle swarm optimization algorithms to evaluate sustainability risks in agricultural supply chains, effectively modeling the nonlinear influence of variables like supplier reliability and fluctuating market demand [59]. In a related domain, [75] proposed an ensemble model using support vector machines enhanced by fuzzy clustering and principal component analysis to evaluate credit risk in supply chain finance. Though not a pure DL model, it aligns well with data preprocessing strategies that are often upstream in DL pipelines, especially in risk scoring applications.

Unstructured and text-rich data sources have also gained traction for real-time risk assessment. One study processed unstructured data from global news feeds to score sourcing risks across apparel supply chains in developing economies, incorporating contextual variables such as labor conditions, political stability, and infrastructure resilience [81]. Building on this idea, another approach used Twitter data with a fuzzy logic-based model to estimate disruption probabilities, illustrating how DL-compatible pipelines leveraging social media can augment responsiveness in dynamic classification systems [82].

At a broader systems level, DL has been applied to assess structural vulnerability and resilience within interconnected supply chain networks. Shen et al. [93] introduced a hypergraph-based neural network to infer supply chain resilience from network topology and historical inventory trajectories, enabling the assessment of systemic exposure to disruptions without explicit modeling of underlying dynamics. By capturing higher-order firm-product dependencies, their approach supports early-stage evaluation of network-level fragility, complementing node-level and event-driven risk assessment models.

Other researchers have leveraged DL to complement simulation frameworks for assessing systemic risk. One hybrid model integrated causal inference techniques with DL to assess supply chain fragility and anticipate ripple effects before disruption propagation [83]. This hybrid approach allowed for risk quantification based not only on historical disruption data but also on inferred causal links between operational variables—bridging the gap between traditional sensitivity analysis and AI-driven prediction. Earlier foundational frameworks, such as those using fuzzy logic with bow-tie analysis, provided structured quantification of risk severity across manufacturing networks, and continue to be conceptually relevant when paired with interpretable DL models [76]. Similarly, simulation-optimization approaches for risk-averse sourcing have been explored. Though not DL-based, this modeling framework can benefit from DL integration in future applications, such as simulating risk scenarios under parameter uncertainty or optimizing sourcing policies using RL [84].

Collectively, these contributions reflect the multidimensional nature of risk assessment in supply chains, where DL methods are being integrated into time-series forecasting, credit scoring, text mining, causal modeling, and simulation-based optimization. The adaptability of DL architectures - along with their ability to handle diverse data formats and evolving conditions—positions them as a natural fit for risk assessment systems that must navigate increasing uncertainty and global interconnectedness.

5.3 Risk Mitigation

Mitigating risks in supply chains involves the implementation of strategies that reduce the severity and propagation of disruptions once identified. DL approaches offer the ability to model adaptive, real-time responses across multiple operational layers, enhancing both resilience and agility. Recent studies have demonstrated how DL architectures, particularly those incorporating reinforcement learning, enable systems to self-adjust procurement, inventory, and distribution strategies under evolving constraints.

Among these, deep reinforcement learning (DRL) has emerged as a dominant paradigm for managing uncertainty through experience-based policy optimization. One study applied DRL to a blockchain-integrated agri-food supply chain, enabling agents to optimize sourcing and distribution routes in real time under conditions of volatile demand and logistics disruptions [72]. The model significantly improved responsiveness and reduced waste compared to traditional planning tools. Another implementation demonstrated a RL-based control system for managing multi-product inventory with varying lead times, achieving scalable and robust policies that dynamically adapted to demand surges and supply delays [73].

The flexibility of DRL has also proven useful in coordinating decentralized decision-making across multiple nodes. A multi-agent DRL approach allowed each agent to learn localized mitigation strategies that collectively improved overall supply chain performance [71]. This decentralized approach enabled adaptive mitigation across complex networks by allowing agents to optimize local actions in alignment with global objectives. Further extending this idea, another study applied multi-agent

DRL to post-disruption recovery planning, focusing on firm-level actions that minimized long-term impacts from catastrophic events [70].

Supplier-side risk mitigation has also benefited from DL-based models. A two-stage architecture was proposed where supervised learning predicted supplier risk indices, which then informed a DRL-powered order allocation system [60]. The resulting hybrid architecture enabled proactive redistribution of procurement volume away from high-risk suppliers, reducing delay propagation. In another application, domain-adapted DL models were employed to ensure quality control in food packaging operations, minimizing labeling errors and compliance failures that could result in downstream penalties or recalls [62].

Recent empirical work has examined the broader role of AI adoption in mitigating supply chain risk at the organizational level. Tian et al. [94] conducted a large-scale empirical analysis of Chinese listed firms, demonstrating that AI adoption is associated with statistically significant reductions in firm-level supply chain risk. Their findings suggest that AI contributes to risk mitigation indirectly by improving resource allocation efficiency, supporting more effective inventory management, supplier coordination, and operational adjustment under uncertainty. While not focused on prescriptive control policies, this evidence complements DL-based mitigation models by highlighting the structural conditions under which learning-enabled systems can reduce risk exposure in practice.

Beyond operational adaptation, DL techniques have also supported strategic risk mitigation through scenario generation and decision support. One study introduced a generative adversarial network (GAN)–augmented optimization system to generate synthetic disruption scenarios, which were used to train a robust supply chain design model [85]. Their system improved resilience under distributional uncertainty by preparing for low-probability, high-impact events. Another approach combines fuzzy logic with neural networks to support preemptive risk scoring, enabling supply chain managers to redesign workflows or resource allocations based on risk exposure levels [57].

DL methodologies have also been linked to improved organizational adaptability and long-term resilience. DRL has been applied to solve the Joint Replenishment Problem, demonstrating how autonomous policy learning can reduce inventory imbalances and enhance coordination among supply nodes [74]. Supporting this perspective, a dual-stage model combining partial least squares structural equation modeling (PLS-SEM) and ANNs demonstrated how DL-enabled agility and real-time data processing contribute to reconfigurable supply chains and upstream delay mitigation [58]. Their findings underscore the potential of DL not only in operational response but also in shaping strategic capabilities for long-term resilience.

Together, these contributions illustrate how DL-driven systems are redefining risk mitigation in supply chains—from supplier selection and inventory balancing to post-disruption recovery and scenario-based planning. As supply chains become increasingly interconnected and data-rich, the ability to adaptively manage risk in real time through learning-enabled architectures marks a fundamental shift in how organizations respond to disruption.

5.4 Risk Monitoring

While risk mitigation focuses on implementing countermeasures, effective SCRM also requires ongoing surveillance of operations to detect deviations or emerging threats. Risk monitoring enables organizations to assess whether existing controls remain effective under evolving conditions and to uncover new risks before they escalate. DL, particularly when combined with real-time data feeds, has emerged as a powerful tool in supporting such continuous oversight across supply chain nodes.

Several studies have demonstrated how DL models, particularly those designed for sequence modeling and anomaly detection, enable supply chains to dynamically monitor operational health. One hybrid framework integrated blockchain with LSTM networks and Analytic Hierarchy Process (AHP) to evaluate sustainable production capabilities in real time [65]. Their approach continuously tracked and ranked supply chain partners using data stored on distributed ledgers, offering a traceable and adaptive mechanism for monitoring risk levels across sourcing tiers. In another instance, machine learning was employed to dynamically select replenishment policies in volatile environments [95]. By adjusting decisions based on real-time input, their system reduced the risk of obsolescence and demand mismatch—problems often overlooked in static forecasting systems.

More recent work has emphasized early warning systems that synthesize heterogeneous data streams to support continuous risk monitoring. Huang [96] developed an AI-driven early warning framework that integrates operational, financial, and external environmental indicators using an ensemble of machine learning and deep learning models, including LSTM networks. Their system continuously updates risk scores and alert levels, enabling organizations to monitor evolving risk conditions with actionable lead times rather than relying on retrospective indicators.

DL models have also proven valuable for multi-modal surveillance, particularly in settings where disruptions manifest across disparate channels. For example, a text mining-based system was used to monitor post-market food safety issues by extracting signals from online media sources [86]. While their primary toolset was NLP-based, the underlying neural models allowed the system to process and extract relevant risk indicators from unstructured data at scale. These models can serve as a blueprint for DL-enabled early warning systems that leverage publicly available sources for rapid disruption sensing.

Other studies have adopted signal-processing and dimension-reduction techniques in tandem with DL. One study implemented a monitoring model based on principal component analysis (PCA) to isolate anomalies in supply chain data [66]. Though PCA itself is a classical method, it can be fused with DL autoencoders to enhance detection precision in high-dimensional data environments. This framework was further adapted to food supply chains, where AI and DL tools continuously monitored parameters such as shelf life, transportation conditions, and temperature exposure to improve resilience [67].

At a system level, digital twin architectures have increasingly been proposed as enabling platforms for continuous risk monitoring. Gabellini et al. [97] conceptualized and validated an intelligent digital twin framework that integrates real-time operational data with predictive analytics to monitor delivery performance, delay risks, and network stability. By maintaining a continuously updated virtual representation of the supply chain, their framework supports ongoing assessment of risk exposure and performance degradation across interconnected nodes.

The role of DL in risk monitoring is further emphasized in systems that aim to rank and categorize risk severity. A multi-criteria decision analysis (MCDA) framework was developed for risk mapping, using traditional statistical tools in a modular structure that accommodates DL-enhanced inputs [14]. This integration becomes particularly valuable when processing large volumes of sensor data, allowing for continuous, adaptive evaluation of risk severity across supply chain nodes.

Together, these studies underscore the growing importance of DL in supporting real-time, adaptive risk monitoring. DL-enabled systems do not merely flag anomalies—they contextualize them, prioritize them, and allow supply chains to respond with agility. As digital infrastructures continue to evolve, integrating DL models into the monitoring phase will be essential for ensuring that mitigation strategies remain effective, relevant, and responsive to new risk patterns as they emerge.

5.5 Cross-Cutting Analysis: Architectural Alignment with Dynamic Risk Characteristics

The preceding Sections 5.1–5.4 have demonstrated how DL architectures support different stages of the SCRM lifecycle. However, a complementary analytical lens reveals deeper systematic patterns: different DL architectures exhibit distinct affinities for specific risk characteristics along the predictability, controllability, and propagation dimensions introduced in Section 3.1. This cross-cutting analysis directly addresses RQ2 by synthesizing architecture - risk alignments across all reviewed applications. Table 4 consolidates this mapping across the three dimensions of our dynamic risk framework. The patterns reveal prescriptive relationships between architectural properties and risk characteristics that transcend individual SCRM stages.

Predictability Alignment The literature demonstrates clear architectural preferences based on risk emergence patterns. Sequential models (LSTM, GRU, BiLSTM, TCN) dominate applications involving gradual occurrence risks, leveraging their inherent ability to capture temporal dependencies and trend evolution [63, 64]. Their memory mechanisms enable detection of slowly deteriorating supplier performance, emerging market volatility, or progressive quality degradation. Conversely, perception-based architectures, particularly CNNs applied to text and image data, are predominantly deployed for sudden occurrence risks [61, 78]. These models excel at extracting discrete risk signals from news feeds, regulatory announcements, and satellite imagery, providing early warning of geopolitical disruptions, natural disasters, or abrupt policy changes.

Controllability Alignment The dimension of control influences both architecture selection and deployment context. Reinforcement learning frameworks are primarily

Table 4 Mapping of deep learning architectures to dynamic risk characteristics

DL architecture	Risk predictability	Risk controllability	Risk propagation	Key applications from literature	Refs
LSTM/GRU/BiLSTM/TCN	Gradual occurrence—excels at detecting patterns evolving over time	Partially controllable—monitors external suppliers and demand trends	Cascading—tracks sequential propagation through supply tiers	Oil import risk assessment, COVID-19 disruption prediction, sustainable production monitoring, lead time forecasting	[64, 65, 72]
CNN (Text & Image)	Sudden occurrence—detects discrete events from news, contracts, regulations	Uncontrollable—identifies external geopolitical and environmental signals	Localized to cascading—identifies origin points before spread	News-based disruption detection, maritime vessel behavior tracking, quality control via image recognition	[61, 62, 78]
ANN/ BPNN	Both gradual and sudden—versatile for various risk patterns	Controllable to partially controllable—evaluates internal operations and suppliers	Localized—typically assesses node-level risks	Supplier risk assessment, sustainable supply chain evaluation, credit risk scoring	[57–60]
Autoencoders	Sudden occurrence—detects anomalies and deviations from normal patterns	Controllable to partially controllable—monitors operational irregularities	Localized—flags individual node anomalies before propagation	Fraudulent transaction detection, operational irregularity identification, supplier behavior monitoring	[66, 67, 89]
RL/ DRL/ MARL	Gradual occurrence—learns from repeated interactions and evolving conditions	Controllable to partially controllable—optimizes decisions within firm's sphere of influence	Cascading to systemic—multi-agent variants handle network-wide coordination	Inventory optimization, supplier diversification, post-disruption recovery, blockchain-integrated supply chains	[68–74]

Table 4 continued

DL architecture	Risk predictability	Risk controllability	Risk propagation	Key applications from literature	Refs
NLP-Enhanced Hybrid	Sudden occurrence—real-time processing of unstructured external signals	Uncontrollable—monitors macro-environmental factors	Systemic—captures widespread disruption signals	Social media sentiment analysis, news-based risk identification, RL with NLP for disruption discovery	[80–82]
GAN-based	Both gradual and sudden—generates synthetic scenarios for rare events	Uncontrollable—prepares for external black swan events	Systemic—models supply network-wide disruptions	Synthetic disruption scenario generation, distributionally robust optimization	[85]
Fuzzy-Neural Hybrid	Gradual occurrence—handles uncertainty in evolving situations	Partially controllable—incorporates expert judgment for external risks	Cascading—bow-tie analysis for propagation pathways	Manufacturing network risk quantification, pre-emptive risk scoring	[57, 76]
Causal Inference + DL	Both gradual and sudden—identifies causal relationships beyond correlations	Partially controllable—distinguishes controllable causes from external factors	Cascading to systemic—models ripple effects through causal chains	Supply chain fragility assessment, ripple effect prediction	[83]

Note: This synthesizes patterns from the reviewed literature Sections 5.1–5.4, mapping deep learning architectures to risk characteristics in our dynamic classification framework (Section 3.1). The mapping reveals systematic alignments between architectural properties and risk dimensions, directly addressing RQ2. Sequential models dominate gradual cascading risks; perception models handle sudden external shocks; reinforcement learning optimizes controllable decisions; hybrid approaches address systemic complexity applied to controllable and partially controllable risk domains where firms retain decision-making authority, such as inventory policies, supplier diversification strategies, and logistics routing [72, 73]. The iterative policy optimization inherent to RL aligns naturally with scenarios where firms can influence outcomes through repeated decisions. In contrast, perception and forecasting models (CNNs, LSTMs) are more commonly deployed for monitoring partially controllable and uncontrollable risks, where the primary objective is accurate prediction rather than direct intervention. Studies by [81] and [80] exemplify this pattern, using NLP-enhanced models to track external labor conditions and market sentiment—factors beyond direct firm control but critical for risk preparedness.

Propagation Alignment Risk propagation characteristics reveal perhaps the most nuanced architectural patterns. Autoencoders and feedforward ANNs dominate applications targeting localized risks at individual supply chain nodes, such as fraud detection, quality control, and supplier-specific performance evaluation [59, 66]. These architectures efficiently process node-level features without requiring network structure modeling. Sequential models appear most frequently in cascading risk contexts, where disruptions propagate through supply chain tiers over time, and their temporal modeling capabilities enable tracking of these sequential effects [65]. Systemic risks, those affecting entire supply networks, increasingly motivate hybrid and multi-agent architectures. Multi-agent DRL enables coordination across decentralized nodes [70, 71], while GAN-based approaches generate synthetic scenarios for network-wide stress testing [85]. The emergence of causal inference integrated with DL [83] represents a frontier in understanding systemic risk propagation pathways.

While certain architectures demonstrate clear affinity for specific risk types, some exhibit remarkable versatility. ANNs appear across nearly all risk categories, though typically in relatively simpler applications compared to specialized architectures. This versatility comes at the cost of requiring careful feature engineering and domain expertise. Conversely, highly specialized architectures, such as CNNs for text or GANs for scenario generation, deliver superior performance in narrow contexts but offer limited transferability. Hybrid approaches attempt to balance these trade-offs by combining complementary architectural strengths, as seen in RL-NLP integration for disruption identification [69] or causal inference with deep neural networks for fragility assessment [83]

This systematic mapping offers practical guidance for organizations designing DL-enabled SCRM systems. Firms facing predominantly gradual, cascading risks from supplier networks should prioritize investment in sequential modeling capabilities and time-series data infrastructure. Organizations exposed to sudden external shocks benefit from perception-based architectures and unstructured data pipelines (e.g., news feeds, social media, satellite imagery). Enterprises with significant control over supply chain decisions gain maximum value from RL frameworks that optimize policies over time. Most realistically, firms face heterogeneous risk portfolios requiring integrated architectures, a finding that motivates the multi-modal AI research direction discussed in Section 8.

6 Real-World Case Studies

The systematic review of academic literature (Sections 3–5) reveals clear patterns of how DL architectures align with dynamic risk characteristics and SCRM lifecycle stages. To validate these findings and illustrate their practical relevance, we now examine how leading organizations have operationalized DL-enabled SCRM systems. These cases demonstrate the translation of architectural capabilities, such as sequential modeling, perception-based detection, and optimization using reinforcement learning, into deployed solutions that address real-world risk management challenges across maritime logistics, financial services, automotive manufacturing, retail, and agriculture.

A relevant example is Maersk, which implemented a cloud-based blockchain system integrated with machine learning (CBML) to enhance transparency, predictive analytics, and sustainability across its global maritime supply chain. As described in [98], ML supports tasks such as ETA (Estimated Time of Arrival) prediction, anomaly detection, and route optimization, while blockchain ensures secure, real-time visibility of transactional records. The system enables reductions in fuel use, improves delay management, and enhances trust among stakeholders, which are all critical components of a resilient and sustainable supply chain. This case highlights how DL, when combined with interoperable digital infrastructure, can move beyond theoretical promise to enable robust, real-time risk management in complex logistical networks.

Another noteworthy real-world application of DL in SCRM is presented in [99], where the authors collaborated with a European automotive manufacturer to develop a predictive framework for weekly delivery delay risk. The study employed a feed-forward neural network trained on real operational supply chain data combined with macroeconomic indicators such as energy prices, inflation rates, and industrial output. By incorporating lagged variables and supply chain KPIs (key performance indicators), the model captured temporal dependencies that are often missed by conventional methods like decision trees and gradient boosting, thereby achieving superior forecasting accuracy. Crucially, the DL-based risk scores were integrated into the firm's tactical planning processes, enabling proactive responses such as inventory reallocation and transport rescheduling. This deployment highlights how DL can translate external economic volatility into timely, actionable insights, reinforcing its value as a core component of resilient and responsive supply chain risk strategies.

Extending this trajectory, DBS Bank [100] offers a compelling example of how AI-driven systems can bolster operational resilience and financial supply chain continuity. By embedding ML into core processes such as credit risk modeling, fraud detection, and transaction monitoring, DBS enhanced its ability to detect disruptions within supplier and partner ecosystems. The bank's approach includes using natural language processing (NLP) models to extract insights from unstructured data, such as contracts and compliance reports, thereby improving transparency and enabling faster risk mitigation decisions. DBS's AI architecture illustrates how DL can play a central role in ensuring liquidity flow and reputational integrity in financial supply chains.

Similarly, FinVolution's [101] deployment of DL in consumer credit risk assessment offers insights for broader supply chain finance applications. Their model leverages behavioral transaction data to generate risk-adjusted lending decisions in near real-time. By automating loan approval for suppliers and retailers operating on thin margins, the firm enhances liquidity and reduces default exposure in the downstream supply chain. The robustness of their predictive analytics platform, trained on millions of customer interactions, demonstrates the scalability of DL-enabled risk evaluation in volatile financial environments, particularly where supplier solvency and order fulfillment reliability are critical.

InstaDeep [102, 103] provides another high-impact case where RL was used to address logistical optimization problems. Collaborating with Deutsche Bahn, InstaDeep developed RL models for train rescheduling and real-time routing, enabling robust performance even under high uncertainty. The company's broader product portfolio, spanning DeepPCB for circuit board routing and DeepChain for drug discovery, underscores the flexibility of DL systems across domains. These industrial deployments showcase how DRL can support operational continuity and throughput maximization in complex, interconnected supply chains.

Zuron [104], a fintech platform supporting micro, small, and medium-sized enterprises (MSMEs), integrates ML models to underwrite supplier credit using alternative data sources such as transactional histories and inventory patterns. By offering real-time credit simulations, the platform supports upstream supplier risk assessment and mitigates fulfillment-related disruptions. This approach not only democratizes access to working capital for underbanked supply chain actors but also enhances the visibility of potential financial bottlenecks that may otherwise propagate downstream.

In the retail sector, Vispera [105] has operationalized DL through computer vision-based solutions for on-shelf availability monitoring, stockout prediction, and planogram compliance. Their system leverages CNNs to process in-store imagery, providing real-time inventory intelligence to suppliers and store managers. By replacing manual audits with automated visual detection, Vispera improves stock rotation, reduces lost sales, and ensures that shelf-level disruptions are flagged before they impact customer experience. This case highlights the value of DL for visibility enhancement in last-mile inventory control.

Bext360 [106] takes a unique approach by combining AI with blockchain to improve traceability in agricultural supply chains. The firm employs DL-based image recognition to evaluate product quality at origin, while blockchain infrastructure provides secure data sharing across stakeholders. This integration ensures that quality degradation, fraud, or ethical sourcing violations are detected early, minimizing both reputational and compliance-related risks. Bext360's model illustrates how DL can play a foundational role in ESG-aligned risk management strategies where transparency and verification are paramount.

Finally, CMA CGM Group's [107] digital transformation highlights the growing role of AI in global logistics orchestration. The company leverages predictive analytics and AI-driven platforms to monitor cargo movements, optimize route planning, and detect early indicators of disruption across its maritime and intermodal networks. These capabilities, underpinned by investment in cloud infrastructure and cybersecurity, enable CMA CGM to reduce schedule variability and buffer inventory risks associated with port congestion and geopolitical volatility. This case affirms the role of enterprise-wide AI integration as a precursor to deploying more advanced DL techniques across global supply chain nodes.

7 Discussion

This systematic review set out to answer four research questions about the role of DL in SCRM. Having examined numerous studies and multiple industrial deployments, we now synthesize the key findings and their implications for both the research community and practitioners.

Our analysis reveals three primary contributions. First, beyond cataloging DL applications across the SCRM lifecycle (RQ3), we identify clear patterns in how DL architectures align with the dynamic characteristics of supply chain risks (RQ2). As synthesized in Table 4 and analyzed in Section 5.5, different DL models exhibit distinct strengths corresponding to risk predictability, controllability, and propagation properties (RQ2). Sequential architectures (LSTM, GRU, TCN) dominate in gradual occurrence and cascading risk contexts, leveraging temporal modeling to track evolving patterns and multi-tier propagation effects. Perception-based models (CNNs, NLP-enhanced architectures) excel at identifying sudden occurrence and uncontrollable risks, extracting early warning signals from unstructured external data. Reinforcement learning frameworks concentrate on controllable and partially controllable domains where iterative policy optimization can influence outcomes. These patterns provide both theoretical insight into why certain architectures succeed in specific contexts and practical guidance for organizations designing risk management systems tailored to their risk profiles.

Real-world deployments further illustrate that DL is not limited to isolated analytical functions, but is increasingly embedded within broader digital ecosystems. Case studies from sectors such as finance, logistics, and retail reveal that DL is being integrated alongside cloud computing, blockchain infrastructure, and enterprise planning tools to deliver end-to-end risk visibility and decision support. This transition from experimental use to operational integration signals a growing maturity in both technological readiness and organizational adoption.

However, despite the observed progress, the application of DL in SCRM remains fragmented, with most implementations targeting narrow problem domains and relying on context-specific datasets. Generalizable frameworks that can accommodate multiple risk types and scale across industries are still relatively rare. Furthermore, the evaluation of DL models often lacks longitudinal analysis or comparative benchmarking against traditional methods, limiting the ability to assess their sustained impact over time.

These observations underscore the need for more holistic research and implementation strategies that bridge methodological development with practical deployment. Key challenges and potential directions for future work are discussed in the following section.

8 Challenges and Future Directions

While our analysis demonstrates significant progress in DL-enabled SCRM, both in academic development and industrial deployment, the field remains far from mature. The patterns identified in Section 5.5 and validated through case studies reveal not only opportunities but also systematic gaps that must be addressed for DL to achieve its transformative potential in SCRM. We organize these challenges around six critical dimensions: data infrastructure, model interpretability, architectural research, framework operationalization, human-AI interfacing, and platform integration. For each, we propose concrete future research directions that address the gaps in our current understanding (RQ4).

Data Infrastructure A fundamental barrier to widespread DL adoption in SCRM is the limited availability of clean, structured, and labeled supply chain data. Many firms operate with fragmented information systems and inconsistent data formats, making it difficult to assemble reliable training datasets. The reliance on extensive preprocessing or proxy variables to compensate for data limitations often degrades model accuracy and generalizability. Future research should explore federated learning architectures that enable model training across distributed data sources without centralized aggregation [108], privacy-preserving techniques such as differential privacy and secure multi-party computation that facilitate collaborative learning while protecting proprietary information [109], and automated data quality assessment frameworks that can identify and flag inconsistencies, missing values, and anomalies in real-time supply chain data streams [110].

Model Interpretability The black-box nature of many DL models undermines stakeholder trust, particularly when model outputs influence high-stakes logistical decisions or risk assessments. As highlighted in [111], supply chain managers often resist adopting DL-driven recommendations they cannot understand or validate against domain expertise. This interpretability challenge is especially acute in SCRM, where decision makers must justify risk mitigation strategies to executives, regulators, and affected stakeholders. The growing field of Explainable artificial intelligence (XAI) offers potential solutions through techniques such as attention mechanisms that highlight which input features drive predictions [112], counterfactual explanations that show how changing specific variables would alter outcomes [113], and local interpretability model-agnostic explanations (LIME) that approximate complex models [114]. Future research should focus on developing SCRM-specific interpretability frameworks that align with supply chain practitioners' mental models and decision-making processes, establishing best practices for communicating model uncertainty and confidence levels in risk predictions, and integrating XAI capabilities directly into DL architectures rather than treating explainability as a post-hoc addition. Enhancing model interpretability can improve accountability, support compliance with regulatory frameworks, and foster greater adoption in risk-averse industries.

Architectural Research While our synthesis reveals systematic patterns in how DL architectures map to dynamic risk characteristics (Table 4), these relationships remain largely implicit in current literature. Future research should explicitly investigate why certain architectural properties align with specific risk dimensions. Comparative studies that systematically vary both risk characteristics and architectural choices would strengthen theoretical understanding and improve prescriptive guidance for practitioners.

The emergence of foundation models and transfer learning raises critical questions about architectural specialization versus generalization. Can pre-trained general-purpose models match or exceed the performance of task-specific architectures across different risk contexts? If so, under what conditions [115]? These questions have significant practical implications, particularly for the resource-constrained organizations that must balance model performance against development and deployment costs [116]. Early evidence from multi-modal foundation models [117] suggests potential for cross-domain transfer, but systematic validation in SCRM contexts remains limited. Furthermore, the generalizability of DL models across firms and industries requires deeper investigation. Models trained in one context often perform poorly in another due to differences in supply chain structure, data characteristics, and risk exposure. Transfer learning and domain adaptation approaches [118] could help improve portability, but remain underexplored in this domain.

Framework Operationalization Our proposed risk classification framework provides conceptual clarity on risk dimensions, but operationalizing these dimensions for practical risk assessment requires further development. Currently, the framework relies on qualitative categorization of risks along predictability, controllability, and propagation dimensions, limiting its utility for systematic, data-driven architecture selection. Future work should focus on developing quantitative metrics for measuring each dimension:

- For predictability, metrics such as forecast error volatility, coefficient of variation, or surprise indices that capture deviation from expected patterns
- For controllability, influence coefficients quantifying the sensitivity of risk outcomes to organizational decisions, decision authority mapping that identifies which risks fall within versus outside managerial control, or hedonic regression approaches that decompose risk variance into controllable and uncontrollable components
- For propagation, network centrality measures identifying critical nodes whose disruption cascades broadly, simulation-based cascade amplification factors, or capturing metrics for connectivity and vulnerability structures

Such quantitative operationalization would enable organizations to objectively match their risk profile to appropriate DL approaches rather than relying on subjective assessment or trial-and-error.

Human-AI Interfacing A closely related but distinct barrier concerns the accessibility of DL-generated risk outputs to the organizational users responsible for acting upon them. Supply chain practitioners, procurement managers, and executives must routinely translate probabilistic risk scores, anomaly flags, and multi-dimensional assessments into concrete operational decisions under time pressure; a translation that demands statistical familiarity with model behavior that most practitioners do not possess. This accessibility gap compounds the model interpretability challenges discussed above. It extends beyond the question of what a model is doing to whether its outputs can be meaningfully interpreted by the people responsible for doing so. It represents a structural impediment to adoption that improvements in predictive accuracy alone cannot resolve. Large language models (LLMs) have emerged as a promising mechanism for addressing this barrier, functioning as a natural language interface layer that converts DL risk outputs into contextual, role-aware narratives without requiring direct engagement with model internals [119]. Recent work has demonstrated the viability of this approach in supply chain contexts, with LLM-enhanced frameworks showing the capacity to integrate structured operational signals with semantically interpreted unstructured inputs to produce risk assessments that are both analytically grounded and communicatively accessible [120]. Simchi-Levi et al. [121] further argue that generative AI is positioned to function not merely as a presentation layer but as an active participant in the supply chain decision process, synthesizing heterogeneous information and adapting outputs to diverse organizational audiences. Future research should investigate the conditions under which LLM-generated narratives faithfully represent the uncertainty and limitations of underlying DL models, the governance frameworks required to deploy such interfaces responsibly in high-stakes decisions, and the design principles for human-AI systems that preserve analytical precision while remaining actionable for non-technical practitioners.

Platform Integration The practical deployment of DL-based risk management methods depends not only on model performance but also on their compatibility within the enterprise systems through which supply chain decisions are executed. A structural tension exists between the task-specific orientation of academic DL models and the way commercial supply chain platforms operationalize risk management implicitly, embedding it within demand sensing, inventory optimization, and control-tower visibility rather than exposing it as a named function. Bridging this gap requires integration architectures capable of coupling DL risk outputs with enterprise resource planning, transportation management, and warehouse management systems in real time, while also maintaining synchronization with evolving data schemas and operational workflows. Digital twin frameworks represent a promising substrate for this coupling [97], providing a continuously updated representation of supply chain state through which model-generated risk intelligence can inform and be acted upon within existing decision processes. In multi-firm contexts, federated learning offers a complementary pathway, enabling collaborative risk model training across organizational boundaries without requiring centralized data aggregation; an approach that has demonstrated viability for privacy-preserving collective risk prediction [122] and order-level risk assessment in supply chain financing [123]. Future research should investigate standardized interoperability protocols that reduce the friction of embedding DL models within heterogeneous enterprise environments, as well as governance frameworks for maintaining model reliability as the underlying data infrastructure evolves.

9 Conclusion

This systematic review demonstrates that DL's value in SCRM extends beyond computational capability to systematic alignments between architectural properties and risk characteristics. By organizing the analysis through a dynamic three-dimensional risk classification framework and examining applications across the complete SCRM lifecycle, we reveal patterns that enable prescriptive guidance for both researchers and practitioners navigating the intersection of AI and supply chain resilience.

The evidence synthesized across academic literature and industrial deployments reveals a field in transition. DL has moved from experimental application in isolated risk management tasks to integrated deployment within enterprise digital ecosystems, as demonstrated by implementations spanning maritime logistics, financial services, automotive manufacturing, and retail. However, the broader literature review reveals that such success stories remain the exception: most implementations target narrow problem domains, rely on context-specific datasets, and lack the generalizability required for widespread adoption. The persistent challenges of data quality, model interpretability, and cross-context transferability continue to limit DL's transformative potential in SCRM.

Looking forward, three trajectories will define the evolution of DL-enabled SCRM. First, the architectural landscape will shift from specialized single-purpose models toward hybrid, multi-modal systems that integrate temporal modeling, perception capabilities, and adaptive decision-making within unified frameworks. Second, the focus will transition from maximizing predictive accuracy to ensuring interpretability, fairness, and robustness-attributes essential for high-stakes supply chain decisions affecting multiple stakeholders. Third, successful adoption will depend less on algorithmic innovation and more on organizational capabilities: building data ecosystems that enable continuous learning, developing governance frameworks for AI-driven decisions, and cultivating expertise that bridges supply chain domain knowledge with DL practice.

The patterns identified in this review provide a foundation for this evolution. By mapping architectural strengths to dynamic risk characteristics, we offer a systematic basis for technology selection and research prioritization. By highlighting persistent gaps in generalizability and interpretability, we define clear directions for methodological advancement. And by documenting both successes and limitations in industrial deployment, we establish realistic expectations for what DL can and cannot currently deliver in SCRM contexts. Realizing the full potential of DL in SCRM requires not only continued algorithmic progress, but fundamental advances in how organizations generate, govern, and act upon AI-driven insights. The roadmap for that journey lies in the systematic alignments revealed through this review.

Author Contribution Roop Harshit Vankayalapati (R.H.V.) and Amarnath Banerjee (A.B.) conceptualized the study and defined the research questions. R.H.V. conducted the systematic literature search, performed data extraction and synthesis, developed the dynamic risk classification framework, and wrote the main manuscript text. R.H.V. prepared all figures and tables. A.B. provided supervision, critical intellectual guidance, and reviewed and revised the manuscript. All authors reviewed and approved the final manuscript.

Data Availability No datasets were generated or analysed during the current study.

Declarations

Conflict of Interest The authors declare no competing interests.

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