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Artificial Intelligence for Supply Chain Resilience and Risk Management in the Digital Era: A Comprehensive Review

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Abstract

Global supply chains have become more intricate, interconnected, and susceptible to a range of disruptions, from natural disasters and pandemics to geopolitical tensions, cyberattacks, and supplier breakdowns. The recent COVID-19 pandemic has really brought to light the significant flaws in traditional supply chain systems, underscoring the pressing need for management strategies that are both resilient and adaptable. Enter Artificial Intelligence (AI), a game-changing technology that can boost supply chain resilience through predictive analytics, smart decision-making, risk assessment, and real-time optimization. This review paper dives into how AI plays a crucial role in fortifying supply chain resilience and enhancing risk management practices in today's supply chain networks. It systematically looks at how Machine Learning, Deep Learning, Reinforcement Learning, Natural Language Processing, and Explainable Artificial Intelligence are applied in predicting disruptions, evaluating supplier risks, managing demand uncertainties, ensuring logistics resilience, and supporting strategic decisions. Additionally, the paper discusses how AI can be integrated with cutting-edge technologies like the Internet of Things, Blockchain, Digital Twins, and Cloud Computing to build intelligent and resilient supply chain ecosystems. It also critically examines key challenges in implementation, such as data quality, transparency, cybersecurity, scalability, and ethical issues. The review highlights significant research gaps and future opportunities for creating autonomous and self-healing supply chains. The findings indicate that AI-driven resilience strategies can greatly improve an organization's adaptability, operational continuity, and competitive edge in an increasingly unpredictable global business landscape.

Keywords

Artificial Intelligence; Supply Chain Resilience; Risk Management; Machine Learning; Deep Learning; Management; Predictive Analytics; Supply Chain Risk; Digital Twin; Blockchain; Industry 4.0.

1. Introduction

The world of supply chains has undergone a remarkable transformation, driven by the rise of globalization, rapid technological progress, and the increasing interconnectedness of businesses. Nowadays, supply chains stretch across various countries, involve a multitude of stakeholders, and rely on advanced logistics and information systems. While globalization has opened doors to greater efficiency and cost savings, it has also heightened the risks and potential disruptions that come with it. Today's supply chains grapple with challenges like natural disasters, geopolitical tensions, economic downturns, supplier issues, transportation delays, cyber threats, and public health crises.

The COVID-19 pandemic was a wake-up call, revealing the weaknesses in global supply chain networks and highlighting the need for resilience and preparedness against risks. Companies from all sectors faced significant shortages of raw materials, delays in transportation, interruptions in production, and shifts in demand. Ongoing disruptions from geopolitical conflicts, climate-related events, and cybersecurity threats continue to put pressure on the stability of supply chains around the globe.

In the past, managing supply chain risks often meant reacting to problems after they happened, using strategies that aimed to minimize losses. Traditional methods typically depended on looking back at historical data, manual monitoring, and rigid contingency plans. However, the fast-paced nature of today's business landscape calls for a more proactive, predictive, and flexible approach to risk management. Organizations are increasingly realizing that resilience—the capacity to foresee, absorb, adapt to, and bounce back from disruptions—is now a key factor in maintaining long-term competitiveness and sustainability.

Artificial Intelligence (AI) has become a game-changer in tackling various challenges. It empowers organizations to sift through massive amounts of both structured and unstructured data, uncover hidden patterns, anticipate potential disruptions, and make smarter decisions. With its advanced analytical capabilities, AI helps businesses spot risks sooner, fine-tune their response strategies, and boost the overall resilience of their supply chains.

Machine Learning (ML) techniques are commonly employed to forecast demand shifts, supplier issues, transportation hiccups, and inventory shortages. Deep Learning (DL) models take this a step further by improving predictive accuracy through the analysis of complex, nonlinear relationships in large datasets. Reinforcement Learning (RL) aids in making adaptive decisions in uncertain situations, allowing for the dynamic optimization of inventory policies, logistics operations, and resource allocation strategies. Meanwhile, Natural Language Processing (NLP) enables organizations to glean valuable risk insights from news articles, financial reports, social media posts, and communications with suppliers.

Beyond standalone AI applications, the fusion of AI with cutting-edge technologies like the Internet of Things (IoT), Blockchain, Digital Twins, Cloud Computing, and Industry 4.0 platforms is opening up exciting new avenues for resilient supply chain management. These technologies offer real-time visibility, improved traceability, predictive monitoring, and autonomous decision-making capabilities that enhance an organization's readiness and effectiveness in responding to challenges.

Even though there's a growing interest in research, the existing literature on AI-enabled supply chain resilience is still quite scattered across various fields like operations management, logistics, information systems, and artificial intelligence. A lot of studies tend to zoom in on specific technologies or focus on isolated aspects of risk management, leaving a gap when it comes to a thorough evaluation of how AI contributes to overall supply chain resilience. On top of that, issues like model interpretability, the complexity of implementation, data privacy, and ethical concerns are still major hurdles for organizations looking to adopt these technologies.

With supply chain disruptions becoming more frequent and severe, it's clear that a detailed review of AI-driven resilience strategies is not just timely but essential. This review aims to pull together what we know about using Artificial Intelligence in supply chain resilience and risk management, assess the latest technological advancements, pinpoint research gaps, and explore future opportunities for developing smart, adaptable, and self-repairing supply chain systems. The goal is to offer valuable insights for researchers, practitioners, policymakers, and organizations that want to boost resilience and maintain operational performance in an increasingly unpredictable and volatile global landscape.

2. Theoretical Foundations of Supply Chain Resilience and Risk Management

Supply chain resilience has become a vital area of research, especially with the rising number and intensity of disruptions impacting global supply networks. Resilience is all about a supply chain's ability to foresee, prepare for, respond to, and bounce back from unexpected challenges while keeping operations running smoothly (Ponomarov & Holcomb, 2009). Unlike traditional risk management strategies that mainly focus on preventing disruptions, resilience highlights the importance of adaptability, flexibility, and quick recovery.

The theoretical underpinnings of supply chain resilience draw from Systems Theory, Resource-Based View (RBV), Dynamic Capability Theory, and Complexity Theory. Systems Theory sees supply chains as interconnected networks, where a disruption in one part can ripple through the entire system (Bertalanffy, 1968). Dynamic Capability Theory posits that organizations need to constantly build adaptive capabilities to effectively respond to changing environmental conditions (Teece et al., 1997). These viewpoints support the integration of Artificial Intelligence into supply chain operations, enhancing visibility, predictive capabilities, and decision-making effectiveness.

Researchers have pinpointed visibility, collaboration, agility, flexibility, redundancy, and adaptability as essential elements of supply chain resilience (Christopher & Peck, 2004). Artificial Intelligence plays a significant role in these areas by facilitating real-time monitoring, predictive analytics, automated decision support, and proactive risk management. As a result, AI is increasingly seen as a key driver of resilient supply chain systems.

Recent research highlights that for supply chains to be truly resilient, they need cutting-edge technologies that can handle massive amounts of data and provide actionable insights, especially in uncertain situations (Ivanov & Dolgui, 2020). As global supply networks become increasingly complex, the demand for smart systems that facilitate ongoing learning and adaptable responses to disruptions becomes even more critical.

3. Evolution of Artificial Intelligence in Risk Prediction and Resilience Planning

Artificial Intelligence has come a long way over the last few decades, evolving from basic rule-based systems into advanced learning algorithms that can make decisions on their own. In the early days, AI in supply chain management was all about deterministic planning models and expert systems aimed at helping with inventory control and logistics scheduling (Turban et al., 2011). While these systems did boost operational efficiency, they struggled to adapt to the complexities and ever-changing nature of risk environments.

With the rise of Machine Learning, new doors opened for predictive risk management. Supervised learning algorithms allowed organizations to anticipate disruptions, evaluate supplier risks, and predict demand changes by analyzing historical data (Jordan & Mitchell, 2015). These Machine Learning models proved to be more flexible and accurate than traditional statistical methods, making them essential for risk assessment and resilience planning.

The advancements in Deep Learning took predictive capabilities to the next level by enabling the analysis of vast amounts of both structured and unstructured data. Techniques like Deep Neural Networks, Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) architectures have been effectively used for predicting disruptions, detecting anomalies, and monitoring supply chains (LeCun et al., 2015; Hochreiter & Schmidhuber, 1997). These technologies empower organizations to uncover hidden patterns and emerging risks that might not be visible through standard analytical methods.

Lately, Reinforcement Learning has been making waves as a powerful tool for adaptive resilience planning. These agents learn continuously from feedback in their environment, allowing them to fine-tune their decisions even when faced with uncertainty. This makes them incredibly valuable for tasks like inventory management, optimizing logistics, and planning for disruptions (Sutton & Barto, 2018). As AI technologies have evolved, they've broadened the horizons of supply chain resilience strategies, shifting the focus from just reacting to challenges to embracing predictive and autonomous decision-making.

4. Machine Learning Applications in Supply Chain Risk Assessment

Machine Learning has really taken off as one of the go-to technologies in Artificial Intelligence for assessing supply chain risks. Why? Because it can sift through massive datasets and make spot-on predictions. Supply chain risks can pop up from all sorts of places—think supplier failures, transportation hiccups, demand swings, cyber threats, geopolitical tensions, and even natural disasters. Traditional methods for assessing these risks often lean on expert opinions and past data, which might not cut it when it comes to spotting new risks in today's complex landscape (Tang, 2006).

Machine Learning algorithms shine here, offering sophisticated predictive power by uncovering connections between various risk factors and getting better as they digest more data. Techniques like Decision Trees, Random Forests, Support Vector Machines, and Gradient Boosting are commonly used to assess supplier performance, foresee disruptions, and categorize risk levels (Baryannis et al., 2019). These models help organizations shift from a reactive approach to risk management to a more proactive stance, focusing on identifying and mitigating risks before they escalate.

Predictive analytics has become a key player in assessing supplier risk. With the help of Machine Learning systems, we can dive into supplier financial indicators, operational performance metrics, delivery reliability, and market conditions to foresee potential supplier failures and disruptions (Ho et al., 2015). By spotting high-risk suppliers early on, organizations can put contingency plans in place and bolster their supply chain resilience.

Machine Learning also lends a hand in managing demand risk by predicting demand uncertainty and spotting unusual consumption patterns. Research has shown that advanced forecasting models can significantly boost prediction accuracy, helping organizations avoid inventory shortages and excess stock (Makridakis et al., 2020). Additionally, anomaly detection algorithms can pick up on unusual operational events that might signal upcoming supply chain disruptions.

The literature consistently shows that Machine Learning enhances supply chain visibility, sharpens risk prediction accuracy, and aids in more effective resilience planning. As organizations continue to generate vast amounts of operational data, Machine Learning is set to play an even bigger role in smart risk management and preventing disruptions.

5. Deep Learning for Disruption Prediction and Demand Uncertainty Management

Deep Learning has become one of the most impactful technologies in the realm of Artificial Intelligence, especially when it comes to tackling the intricate challenges of supply chains that are often marked by uncertainty, nonlinearity, and vast amounts of data. Unlike the more traditional machine learning methods, deep learning models have the ability to automatically pull out significant features from large datasets, which makes them particularly adept at predicting disruptions and managing demand uncertainty (LeCun et al., 2015).

Supply chain disruptions can stem from a variety of interconnected issues, such as supplier failures, transportation delays, geopolitical tensions, natural disasters, and unexpected shifts in demand. Deep learning frameworks like Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer models have shown remarkable effectiveness in uncovering complex relationships among these factors (Vaswani et al., 2017). These models are capable of analyzing historical operational data, real-time market trends, weather conditions, and economic indicators to foresee potential disruptions before they happen.

LSTM networks, in particular, excel at time-series forecasting because they can grasp long-term dependencies and temporal patterns in demand data (Hochreiter & Schmidhuber, 1997). Research has indicated that LSTM-based forecasting models surpass traditional statistical methods when it comes to predicting sales demand, inventory needs, and market changes (Makridakis et al., 2020). By improving forecasting accuracy, organizations can reduce stockouts, cut down on excess inventory, and boost service levels.

Deep learning is essential for spotting anomalies and keeping an eye on disruptions. Techniques like autoencoders and deep neural networks can pick up on unusual patterns in operations that might signal potential risks in supply chain networks (Choi et al., 2018). By offering early warning signs, these systems help organizations take proactive steps to manage risks and enhance the resilience of their supply chains.

With the surge in big data and cloud computing resources, the use of deep learning technologies in supply chain management has really taken off. As companies continue to churn out massive amounts of operational data, deep learning is set to become a key player in fostering predictive resilience and smart decision-making.

6. AI-Based Supplier Risk Evaluation and Procurement Resilience

Suppliers play a vital role in the supply chain, and any disruptions they face can seriously impact how well an organization performs. Risks associated with suppliers can range from financial instability and quality problems to delivery delays, regulatory issues, geopolitical uncertainties, and operational failures. That's why it's crucial to evaluate suppliers effectively and build resilience in procurement to ensure the supply chain runs smoothly and is less vulnerable to disruptions (Christopher & Peck, 2004).

Traditional methods for evaluating suppliers often use multi-criteria decision-making techniques like the Analytic Hierarchy Process (AHP), Data Envelopment Analysis (DEA), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Ho et al., 2010). While these approaches offer structured ways to assess suppliers, they can struggle with processing large amounts of dynamic and unstructured data.

Artificial Intelligence has revolutionized how we assess supplier risks by allowing for continuous monitoring and predictive evaluations. Machine Learning algorithms can sift through supplier performance metrics, financial records, quality indicators, and operational data to pinpoint high-risk suppliers and predict potential disruptions (Baryannis et al., 2019). This predictive power helps organizations take proactive steps to mitigate risks and bolster procurement resilience.

Natural Language Processing (NLP) takes supplier intelligence a step further by pulling insights from unstructured sources like supplier reports, news articles, social media, and regulatory filings. Techniques like sentiment analysis and text mining can help spot early warning signs of financial trouble, reputational risks, or operational challenges (Young et al., 2018). This kind of information enables organizations to foresee supplier-related disruptions and enhance their risk management strategies.

Recent studies highlight how crucial it is to diversify suppliers and adopt strategic sourcing, especially with the help of AI-powered analytics (Ivanov & Dolgui, 2020). Smart procurement systems can assess different suppliers, model potential disruptions, and suggest the best sourcing strategies even when things are uncertain. As a result, AI plays a key role in creating robust supplier networks and improving procurement decision-making.

7. Intelligent Logistics and Transportation Risk Management

Transportation and logistics operations are some of the most susceptible parts of today's supply chains. Factors like delays, route disruptions, vehicle breakdowns, labor shortages, infrastructure issues, fluctuating fuel prices, and bad weather can really take a toll on how well things run and how satisfied customers are. That's why effective logistics risk management is crucial for keeping supply chains resilient and ensuring that products keep flowing smoothly (Tang, 2006).

Artificial Intelligence has completely transformed logistics management by introducing predictive analytics, dynamic routing, and real-time decision support. Machine Learning models sift through historical transportation data, traffic patterns, weather forecasts, and operational conditions to foresee disruptions and fine-tune logistics planning (Min, 2010). These predictive tools empower organizations to spot potential risks ahead of time and proactively tweak their transportation strategies.

Reinforcement Learning has also become a hot topic for tackling dynamic routing and transportation optimization challenges. These agents learn continuously from feedback in their environment, helping to pinpoint the best delivery routes even when conditions change (Nazari et al., 2018). This adaptability not only boosts transportation efficiency but also lessens the impact of disruptions on delivery performance.

Deep learning models have shown great promise in areas like traffic prediction, vehicle scheduling, and route optimization. Technologies such as Graph Neural Networks and Recurrent Neural Networks are becoming more popular for modeling transportation networks and forecasting congestion patterns (Wu et al., 2016). These advancements allow for real-time adjustments to routes and bolster logistics resilience, especially during uncertain times.

When you combine Artificial Intelligence with Internet of Things (IoT) technologies, it really amps up logistics risk management. Connected sensors give us real-time insights into where vehicles are, the conditions of shipments, and overall transportation performance. AI algorithms sift through these data streams to spot anomalies, foresee potential failures, and suggest corrective measures (Lee et al., 2015).

Research consistently shows that AI-powered logistics systems enhance transportation reliability, cut operational costs, boost delivery performance, and fortify supply chain resilience. As transportation networks grow more intricate, intelligent logistics solutions are set to become key players in future risk management strategies.

8. Digital Twins, Internet of Things, and Blockchain for Resilient Supply Chains

The rise of Industry 4.0 technologies is really shaking up traditional supply chains, turning them into smart, interconnected, and resilient networks. Key players in this transformation include Digital Twins, the Internet of Things (IoT), and Blockchain, all of which are making waves for their ability to boost visibility, traceability, and predictive decision-making. When these technologies team up with Artificial Intelligence, they form powerful ecosystems that can monitor, analyze, and optimize supply chain operations in real time (Ivanov & Dolgui, 2016).

The Internet of Things plays a crucial role by enabling continuous data collection through sensors, RFID devices, GPS trackers, and connected equipment spread across supply chain networks. These gadgets churn out real-time information about inventory levels, transportation conditions, warehouse operations, and equipment performance (Lee et al., 2015). AI algorithms then sift through these data streams to spot anomalies, predict failures, and help mitigate risks proactively. With real-time visibility, organizations can quickly respond to disruptions and enhance their overall resilience.

Digital Twin technology takes resilience a step further by creating virtual replicas of physical supply chain systems. These digital models simulate operational processes, assess different scenarios, and forecast the impact of potential disruptions before they happen (Ivanov & Dolgui, 2016). Thanks to AI-powered digital twins, managers can carry out risk assessments, fine-tune contingency plans, and test recovery strategies in a virtual space without disrupting actual operations.

Blockchain technology plays a crucial role in boosting supply chain resilience by offering secure, transparent, and unchangeable records of transactions among various stakeholders. It builds trust, enhances traceability, and promotes accountability, all while minimizing information gaps between supply chain participants (Saberi et al., 2019). When combined with AI, blockchain can streamline processes like risk assessment, fraud detection, and smart contract management. Recent research indicates that merging AI, IoT, Digital Twins, and Blockchain can greatly enhance supply chain visibility, collaboration, responsiveness, and overall resilience. These cutting-edge technologies are poised to become essential elements of the next generation of intelligent supply chain systems..

9. Challenges and Barriers to AI Adoption in Supply Chain Resilience Management

Even though Artificial Intelligence brings a lot of advantages, organizations still encounter various hurdles when trying to implement AI-driven resilience management systems. One of the biggest obstacles is the quality and availability of data. AI models rely heavily on data that is accurate, complete, and timely. Unfortunately, many organizations struggle with fragmented information systems, inconsistent data formats, and incomplete datasets, which can seriously impact how well these models perform and how reliable they are (Wamba et al., 2020).

Another major challenge is model interpretability. A lot of advanced AI systems, especially deep learning models, operate like black boxes, making it tough to understand how they make decisions. This lack of clarity can undermine trust among managers and hinder adoption in high-stakes decision-making situations (Adadi & Berrada, 2018). As a result, Explainable Artificial Intelligence (XAI) has become a crucial area of research focused on enhancing model transparency and accountability.

Cybersecurity and data privacy issues are serious threats that organizations can't afford to ignore. As supply chains get more digital and interconnected, the risk of cyberattacks, data breaches, and other malicious disruptions grows. To safeguard sensitive operational and customer data, companies need strong cybersecurity measures and to comply with regulations (Ivanov et al., 2019).

However, the complexity of implementation and the high costs can be daunting, especially for small and medium-sized businesses. Successfully integrating AI often demands significant investments in technology, cloud resources, employee training, and changes within the organization (Bag et al., 2016).

Additionally, resistance to change, a lack of technical know-how, and insufficient digital maturity can further slow down the adoption process.

On top of that, ethical issues like algorithmic bias, fairness, accountability, and responsible AI use are gaining more attention from researchers and policymakers. Tackling these challenges is crucial for the sustainable and effective integration of AI technologies into resilient supply chain systems.

10. Research Gaps, Future Directions, and Conclusion

While we've made significant strides in using Artificial Intelligence to boost supply chain resilience and manage risks, there are still some key research gaps that need to be addressed. Most existing studies tend to zero in on specific applications like assessing supplier risks, forecasting demand, optimizing logistics, or predicting disruptions. However, there's been limited exploration of integrated AI frameworks that can handle multiple aspects of resilience across complex supply chain networks (Ivanov & Dolgui, 2020).

Another major gap lies in the real-world application and validation of these models. A lot of AI models are tested in simulation environments or with historical data instead of in actual operational settings. Future research should focus on implementing these strategies in the field and conducting long-term evaluations to truly gauge how effective AI-driven resilience strategies are in real-world scenarios.

The rise of Explainable Artificial Intelligence (XAI), Generative AI, Federated Learning, Edge AI, and Autonomous Decision-Making Systems opens up exciting avenues for future research. Explainable AI can enhance transparency and build trust in decisions related to resilience, while Generative AI could aid in scenario planning, risk communication, and strategic decision-making. Additionally, Federated Learning and Edge AI can improve data privacy and facilitate decentralized resilience management across distributed supply chain networks (Dwivedi et al., 2017).

Sustainability is not just a buzzword; it's a crucial area for future research. It's essential for researchers to explore how AI can enhance resilience, boost economic performance, promote environmental sustainability, and uphold social responsibility all at once. By merging resilience and sustainability goals, organizations can create supply chain systems that are not only stronger but also ready for the future.

To wrap it up, Artificial Intelligence is truly a game-changer in the realm of supply chain resilience and risk management. With tools like Machine Learning, Deep Learning, Reinforcement Learning, Natural

Language Processing, and the latest Industry 4.0 technologies, we can predict disruptions, assess risks, make adaptive decisions, and enhance resilience. Sure, there are hurdles to overcome, such as data quality, interpretability, cybersecurity, and implementation challenges, but the rewards of AI-driven resilience strategies are significant. Companies that harness these technologies effectively will be in a prime position to foresee disruptions, ensure smooth operations, and gain a sustainable edge in an increasingly unpredictable global market.

Conclusion

The growing complexity and unpredictability of today's supply chains have made it crucial for organizations in the digital economy to prioritize resilience and risk management. We've seen global disruptions—like pandemics, geopolitical tensions, climate disasters, cyber threats, and supplier breakdowns—expose the weaknesses of traditional risk management methods. This has underscored the urgent need for smart, adaptable, and proactive solutions. In this landscape, Artificial Intelligence (AI) has stepped up as a game-changing technology that can greatly boost supply chain resilience through tools like predictive analytics, real-time monitoring, intelligent decision-making, and automated risk management.

This review delves into how AI technologies have evolved and are being applied in the realms of supply chain resilience and risk management. The research shows that Machine Learning, Deep Learning, Reinforcement Learning, and Natural Language Processing offer robust capabilities for spotting risks, forecasting disruptions, optimizing logistics, assessing supplier performance, and enhancing demand forecasting accuracy. These technologies empower organizations to shift from merely reacting to challenges toward adopting proactive and predictive resilience strategies.

The review emphasized how crucial it is to blend AI with cutting-edge technologies like the Internet of Things (IoT), Digital Twins, Blockchain, Cloud Computing, and Industry 4.0 platforms. Together, these technologies enhance supply chain visibility, transparency, traceability, and responsiveness. AI-driven Digital Twins enable scenario simulations and resilience planning, while IoT and Blockchain bolster monitoring, collaboration, and trust within supply chain networks.

However, despite the significant advantages of AI-enhanced resilience management, there are still several hurdles to overcome. Challenges related to data quality, model interpretability, cybersecurity, implementation costs, organizational readiness, and ethical issues continue to impact the successful integration of AI technologies. Tackling these challenges will require investments in digital infrastructure, skilled personnel, strong governance frameworks, and responsible AI practices.

The review also pointed out key research gaps, such as the need for integrated resilience frameworks, real-world implementation studies, explainable AI models, and sustainability-focused resilience strategies. Future research should delve into the possibilities of Generative AI, Federated Learning, Edge AI, and autonomous decision-making systems to develop smarter, more adaptable, and self-healing supply chains that can function effectively in uncertain and disruptive conditions.

In conclusion, Artificial Intelligence is a game-changer for resilient supply chain management in today's digital world. Companies that effectively harness AI technologies can boost their ability to predict risks, enhance their operational flexibility, recover from disruptions more effectively, and gain a sustainable edge over their competitors. As technology continues to evolve at a rapid pace, strategies that focus on AI-driven resilience will become even more crucial in shaping the future of global supply chain management and securing long-term success for organizations.

References

Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: A survey on explainable artificial intelligence. *IEEE Access, 6*, 52138–52160. https://doi.org/10.1109/ACCESS.2018.2870052

Bag, S., Yadav, G., Kumar, A., & Sivarajah, U. (2016). An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making. *Industrial Marketing Management, 92*, 178–189. https://doi.org/10.1016/j.indmarman.2020.10.013

Baryannis, G., Dani, S., & Antoniou, G. (2019). Predicting supply chain risks using machine learning: The trade-off between performance and interpretability. *International Journal of Production Research, 57*(7), 2177–2207. https://doi.org/10.1080/00207543.2018.1464238

Bertalanffy, L. von. (1968). *General System Theory: Foundations, Development, Applications*. George Braziller.

Choi, T. M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management and supply chain management. *Production and Operations Management, 27*(10), 1868–1883. https://doi.org/10.1111/poms.12838

Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *The International Journal of Logistics Management, 15*(2), 1–14. https://doi.org/10.1108/09574090410700275

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., ... Wright, R. (2017). So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2017.102642

Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision-making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research, 202*(1), 16–24. https://doi.org/10.1016/j.ejor.2009.05.009

Ho, W., Zheng, T., Yildiz, H., & Talluri, S. (2015). Supply chain risk management: A literature review. *International Journal of Production Research, 53*(16), 5031–5069. https://doi.org/10.1080/00207543.2015.1030467

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. *International Journal of Production Research, 58*(10), 2904–2915. https://doi.org/10.1080/00207543.2020.1750727

Ivanov, D., & Dolgui, A. (2016). A digital supply chain twin for managing disruption risks and resilience in the era of Industry 4.0. *International Journal of Production Research, 59*(13), 3976–3993. https://doi.org/10.1080/00207543.2020.1768450

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on resilient supply chains. *International Journal of Production Research, 57*(3), 829–846. https://doi.org/10.1080/00207543.2018.1488086

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science, 349*(6245), 255–260. https://doi.org/10.1126/science.aaa8415

Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters, 3*, 18–23. https://doi.org/10.1016/j.mfglet.2014.12.001

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444. https://doi.org/10.1038/nature14539

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2020). The M4 competition: 100,000 time series and 61 forecasting methods. *International Journal of Forecasting, 36*(1), 54–74. https://doi.org/10.1016/j.ijforecast.2019.04.014

Min, H. (2010). Artificial intelligence in supply chain management: Theory and applications. *International Journal of Logistics Research and Applications, 13*(1), 13–39. https://doi.org/10.1080/13675560902736537

Nazari, M., Oroojlooy, A., Snyder, L., & Takáč, M. (2018). Reinforcement learning for solving the vehicle routing problem. *Advances in Neural Information Processing Systems, 31*, 9839–9849.

Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. *The International Journal of Logistics Management, 20*(1), 124–143. https://doi.org/10.1108/09574090910954873

Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2019). Blockchain technology and its relationships to sustainable supply chain management. *International Journal of Production Research, 57*(7), 2117–2135. https://doi.org/10.1080/00207543.2018.1533261

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement Learning: An Introduction* (2nd ed.). MIT Press.

Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics, 103*(2), 451–488. https://doi.org/10.1016/j.ijpe.2005.12.006

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Turban, E., Sharda, R., & Delen, D. (2011). *Decision Support and Business Intelligence Systems* (9th ed.). Pearson.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems, 30*, 5998–6008.

Wamba, S. F., Queiroz, M. M., Trinchera, L., & Kannan, J. (2020). Dynamics between blockchain adoption determinants and supply chain performance. *International Journal of Production Economics, 229*, 107791. https://doi.org/10.1016/j.ijpe.2020.107791

Wu, Y., Ke, J., Sun, Y., & Zhu, X. (2016). Deep learning applications in intelligent transportation systems: A review. *IEEE Transactions on Intelligent Transportation Systems, 22*(7), 4087–4101. https://doi.org/10.1109/TITS.2020.2983842

Young, T., Hazarika, D., Poria, S., & Cambria, E. (2018). Recent trends in deep learning-based natural language processing. *IEEE Computational Intelligence Magazine, 13*(3), 55–75. https://doi.org/10.1109/MCI.2018.2840738