World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

AI Driven Resilience Framework for U.S. Manufacturing Supply Chain Optimization: Bridging technological excellence with intelligent automation and advanced analytics

Samuel Sunday Omotoso *

Department of Information Systems, University of Arkansas, Fayetteville.

World Journal of Advanced Research and Reviews, 2025, 27(03), 342–350

Publication history: Received on 22 July 2025; revised on 03 September 2025; accepted on 05 September 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.27.3.3113

Abstract

Global supply chain disruptions, amplified by the COVID 19 pandemic and geopolitical tensions, have highlighted vulnerabilities in U.S. manufacturing systems, especially in sectors critical to national security and public health. To address these challenges, this study developed a simulation-based Artificial Intelligent (AI) driven resilience framework integrating predictive analytics, autonomous response systems, and digital thread architectures. A mixed methods approach was employed: qualitative insights were obtained through a systematic review of peer reviewed literature and policy reports, while quantitative findings were derived from simulation experiments using synthetic disruption datasets. The simulations demonstrated that Long Short-Term Memory (LSTM) networks outperformed Random Forest and XGBoost in disruption forecasting, achieving the highest predictive accuracy. Similarly, Deep Reinforcement Learning (DRL) simulations suggested a reduction in recovery time by nearly 40% and operational cost savings of approximately 18% when compared with baseline rule-based systems. Furthermore, simulated digital thread integration improved supply chain visibility, traceability, and coordination efficiency by over 25 points on average relative to traditional systems. While these outcomes were generated in a simulated environment rather than validated through real world datasets, the findings reinforced the feasibility and potential of AI driven resilience frameworks. The study contributes theoretically by conceptualizing resilience as a proactive, adaptive capability, and practically by providing evidence that such frameworks could support reshoring strategies, reduce foreign dependencies, and strengthen U.S. supply chain readiness.

Keywords: Machine Learning; Deep Reinforcement Learning; Long Short-Term Memory; Predictive Analytics; Intelligent Automation; Advanced Analytics

1. Introduction

Resilient supply chains are indispensable for U.S. national security and public health. The COVID 19 pandemic exposed systemic fragility, with shortages in pharmaceuticals, semiconductors, and protective medical equipment underscoring the nation's dependence on global suppliers. Geopolitical disruptions, such as trade wars and energy crises, have further amplified vulnerabilities, threatening the stability of critical industries (Zamani, Smyth, Gupta, and Dennehy, 2023). In this context, AI and advanced analytics are being explored as key enablers of supply chain resilience, offering capabilities for predictive disruption management, lifecycle transparency, and reshoring of manufacturing. The U.S. has placed renewed emphasis on reshoring essential manufacturing capacity to mitigate foreign dependencies. Digital transformation tools particularly digital thread architectures, predictive analytics, and autonomous AI systems hold promise for enabling localized, agile, and adaptive supply chains (Belhadi, Mani, Kamble, Khan, and Verma, 2021). By embedding intelligence across product lifecycles, AI driven frameworks can enhance visibility, flexibility, and responsiveness, reducing the cascading risks of disruptions. Recent scholarship has emphasized AI's contribution to the

* Corresponding author: Samuel Sunday Omotoso

four resilience phases: readiness, response, recovery, and adaptability. In a systematic review, Zamani et al. (2023) found that AI and big data analytics (BDA) significantly strengthen predictive capacity, enabling organizations to detect and mitigate risks before they materialize. Complementarily, Belhadi et al. (2021) demonstrated empirically that AI driven innovations improve performance under volatile conditions, supporting organizational agility and robustness.

Emerging technologies such as deep reinforcement learning (DRL) further extend these capabilities by allowing supply chains to autonomously optimize responses to real time disruptions. Kalusivalingam, Sharma, Patel, and Singh (2024) highlight that DRL models, when integrated with predictive analytics, can dynamically adjust logistics flows under uncertain environments. Similarly, Jahin, Naife, Saha, and Mridha (2023) reviewed machine learning applications in supply chain risk assessment, concluding that hybrid AI models (e.g., Random Forest, XGBoost) improve predictive precision compared to traditional methods. Another key enabler of resilience is the digital thread, a data architecture connecting all stages of a product lifecycle from design and engineering to logistics and maintenance. By ensuring real time, end to end traceability, digital threads provide supply chains with dynamic visibility and adaptability (National Institute of Standards and Technology [NIST], 2024). Industry adoption is accelerating. The Manufacturing Leadership Council (2025) reported that digital thread adoption is directly correlated with increased agility and faster recovery from disruptions. Similarly, Siemens Government Technologies (2025) stressed that digital twins and digital thread integration are central to reshoring efforts, particularly for defense critical manufacturing. Aras's 2024 industry survey confirmed that nearly 90% of firms now recognize the digital thread as foundational for scaling AI and automation (IT Supply Chain, 2025). Reshoring initiatives are increasingly framed as essential to national resilience. By integrating AI with digital twin and digital thread frameworks, U.S. manufacturers can strengthen localization, streamline processes, and reduce exposure to foreign supply networks. However, caution is warranted: the Organisation for Economic Co operation and Development (OECD, 2025) warns that overly aggressive reshoring could introduce new inefficiencies and GDP risks, suggesting that resilience strategies must balance domestic autonomy with global diversification. Despite growing interest in AI driven resilience, U.S. supply chains remain fragmented, with limited interoperability and slow adoption of autonomous systems. Existing resilience strategies are largely reactive, lacking predictive capacity and proactive decision making. The gap is clear: there is no comprehensive framework that integrates predictive AI, autonomous response, and digital thread architectures for reshoring and national security purposes.

The objective of this study is to develop an AI Driven Resilience Framework for U.S. manufacturing supply chains, leveraging predictive analytics, autonomous AI systems, and digital thread integration. The framework will focus on industries critical to national security and public health. Specifically, this research aims to:

- Design predictive AI models to forecast and mitigate supply chain disruptions.
- Develop digital thread architectures to improve visibility and lifecycle integration.
- Evaluate the role of AI in reshoring, reducing foreign dependence and enhancing resilience.

1.1. Research Questions (RQs)

- RQ1: How can AI driven predictive models enhance disruption anticipation and mitigation in critical U.S. supply chains?
- RQ2: What role does digital thread integration play in real time visibility, traceability, and autonomous control?
- RQ3: Can AI based frameworks facilitate reshoring and national supply chain sovereignty?

This study contributes to both academic and policy discourses by bridging AI research, supply chain management, and industrial strategy. For national security, resilient AI driven supply chains safeguard defense readiness and public health preparedness. For industry, the framework can transform supply chains into anticipatory, cognitive networks, aligning with Industry 4.0 principles. Ultimately, this research will provide both theoretical and practical pathways for leveraging intelligent automation to reduce foreign reliance while maintaining global competitiveness.

2. Literature review

Artificial intelligence (AI) has increasingly been recognized as a transformative force in enhancing supply chain resilience. According to Zamani, Smyth, Gupta, and Dennehy (2023), AI and big data analytics (BDA) significantly strengthen resilience across the readiness, response, recovery, and adaptability phases by enabling predictive insights and proactive decision making. Similarly, research by Belhadi, Mani, Kamble, Khan, and Verma (2021) demonstrates that AI driven innovations improve both supply chain performance and resilience, particularly under volatile and uncertain conditions. Predictive analytics, supported by AI, provides the ability to anticipate disruptions and demand fluctuations with greater accuracy. Kalusivalingam, Sharma, Patel, and Singh (2024) highlight the role of deep reinforcement learning (DRL) in enabling autonomous adaptation of supply chains to sudden changes in supply and demand. Likewise, Jahin, Naife, Saha, and Mridha (2023) conducted a systematic review of AI in supply chain risk assessment, showing that hybrid machine learning approaches such as Random Forest and XGBoost outperform traditional risk evaluation methods. These findings collectively suggest that AI not only enhances reactive responses but also shifts supply chain management toward predictive and prescriptive approaches. Parallel to AI developments, the digital thread has emerged as a critical enabler of resilience. The digital thread refers to an integrated data architecture that connects product lifecycle information across design, engineering, manufacturing, and logistics. A systematic review by Singh and Willcox (2024) defines the digital thread as essential for eliminating data silos and enabling end to end visibility and traceability across supply chains.

Industry focused studies reinforce this academic perspective. The Manufacturing Leadership Council (2025) reports that firms adopting digital thread practices have achieved greater agility, visibility, and operational accuracy. Similarly, the National Institute of Standards and Technology (2024) emphasizes that the digital thread provides a “single source of truth” for manufacturing and logistics data, enhancing collaboration and resilience. In addition, a framework proposed by Pistikopoulos et al. (2025) demonstrates how integrating digital thread architectures with AI based predictive analytics can provide decision makers with real time, data driven insights to optimize supply chain resilience. The convergence of AI and digital thread architectures is increasingly recognized as foundational for resilient and autonomous supply chains. According to Jahin et al. (2023), AI requires robust, high quality data streams to function effectively, and the digital thread provides the necessary infrastructure to support such data integration. Conversely, the predictive capabilities of AI enable the digital thread to evolve from a passive data repository into an active decision support mechanism. Furthermore, Siemens Government Technologies (2025) highlights how digital thread technologies, when integrated with AI driven predictive models, can facilitate reshoring of manufacturing by ensuring that domestic operations are both transparent and agile. This alignment suggests that the synergy of AI and digital thread not only enhances resilience but also supports strategic national objectives of reducing foreign dependence while maintaining competitiveness.

3. Methodology

3.1. Research Design

This study adopted a mixed methods research design, combining both qualitative and quantitative approaches. The qualitative component involved a systematic review of published research and policy documents on AI driven supply chain resilience. The quantitative component involved simulation-based modeling and analysis using synthetic datasets that reflected disruption scenarios in U.S. manufacturing supply chains. This design was selected to provide both theoretical insights and empirical validation, as resilience involves socio organizational as well as technical dimensions.

3.2. Data Collection

3.2.1. Qualitative Data

The qualitative data were collected through a systematic literature review (SLR). Peer reviewed papers published between 2018 and 2025 were extracted from Web of Science, Scopus, PubMed, and IEEE Xplore. Inclusion criteria were: (a) relevance to supply chain resilience, (b) focus on AI, predictive analytics, or digital thread frameworks, and (c) case studies or empirical investigations involving manufacturing sectors critical to national security and public health. Government publications, such as the *NIST Roadmap to Strengthen Supply Chains* (National Institute of Standards and Technology [NIST], 2024), and industry reports were also included to capture applied perspectives. The selected articles were thematically coded using NVivo 14, which supported identification of recurring themes such as “predictive analytics in disruption management,” “autonomous response systems,” and “digital thread for lifecycle integration.”

3.2.2. Quantitative Data

For the quantitative component, synthetic datasets were generated to simulate supply chain disruptions in three critical industries: pharmaceuticals, semiconductors, and defense manufacturing. The datasets were modeled to reflect typical supply chain parameters such as demand fluctuations, supplier reliability, transportation lead times, and disruption events (e.g., factory shutdowns, cyberattacks). These datasets were informed by case descriptions available in prior empirical studies (Belhadi, Mani, Kamble, Khan, and Verma, 2021; Zamani, Smyth, Gupta, and Dennehy, 2023).

3.3. Analytical Framework

The analysis followed a three-layered framework

3.3.1. Predictive Analytics Layer

Machine learning algorithms, including Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks, were trained to predict disruption events. Historical disruption case data (sourced from literature) were encoded into synthetic datasets, which allowed the algorithms to be evaluated on accuracy, precision, recall, and F1 scores (Jahin, Naife, Saha, and Mridha, 2023).

3.3.2. Autonomous Response Layer

A deep reinforcement learning (DRL) model was implemented to simulate autonomous decision making. The DRL agent was trained in a simulated supply chain environment (using AnyLogic) to optimize logistics rerouting, supplier switching, and inventory redistribution under uncertainty (Kalusivalingam, Sharma, Patel, and Singh, 2024).

3.3.3. Digital Thread Integration Layer

A simulated Product Lifecycle Management (PLM) environment was established to integrate the predictive and autonomous systems. The digital thread linked data across design, manufacturing, and logistics stages, providing continuous lifecycle traceability. This integration was aligned with the frameworks recommended by Singh and Willcox (2024).

3.4. Tools and Techniques

The following tools and techniques were employed

- Python (TensorFlow, PyTorch, scikit learn): for predictive and reinforcement learning model development.
- AnyLogic: for discrete events and agent-based supply chain simulations.
- NVivo 14: for qualitative coding and thematic analysis of literature.
- Tableau and Matplotlib: for visualization of model outputs.
- Simulated PLM Platform: to test digital thread integration.

3.5. Data Analysis Strategy

The qualitative data were analyzed through thematic analysis, which identified patterns across academic and policy literature. These themes provided conceptual grounding for the framework.

The quantitative data were analyzed through statistical evaluation of AI model performance, measuring accuracy, precision, recall, and F1 scores. The DRL model was analyzed in terms of its ability to reduce disruption recovery time, optimize rerouting decisions, and balance cost efficiency against resilience. The digital thread simulation was assessed for improvements in visibility, traceability, and coordination across supply chain nodes.

3.6. Evaluation Metrics

- The effectiveness of the AI driven resilience framework was measured using:
- Prediction Accuracy: evaluated through precision, recall, and F1 scores of predictive models.
- Response Effectiveness: measured by reduction in lead times and improved supplier switching success rates.
- Recovery Time Objective (RTO): the time taken for simulated supply chains to return to operational stability.
- Resilience Index: a composite measure combining agility, flexibility, and robustness, based on Ponomarov and Holcomb (2009).
- Cost Impact: assessment of cost savings versus resilience gains.

Limitations

This study was limited by its reliance on synthetic datasets, which may not capture the full complexity of real-world disruptions. Furthermore, the digital thread was modeled in a simulated PLM environment, which may differ from actual enterprise adoption challenges (NIST, 2024). Finally, while AI models demonstrated predictive and adaptive capabilities, human oversight remained a necessary factor, aligning with concerns raised by Kamble, Khan, and Verma (2021) regarding over reliance on automation.

4. Results

4.1. Predictive Analytics Outcomes

The predictive analytics models were evaluated using synthetic disruption datasets. Among the tested models, the LSTM neural network outperformed Random Forest and XGBoost in terms of accuracy, precision, recall, and F1 score. This suggests that LSTM models were more effective in capturing temporal dependencies in supply chain disruptions.

Table 1 Performance of Predictive Models in Supply Chain Disruption Forecasting

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	0.87	0.85	0.83	0.84
XGBoost	0.91	0.89	0.88	0.88
LSTM	0.94	0.92	0.91	0.92

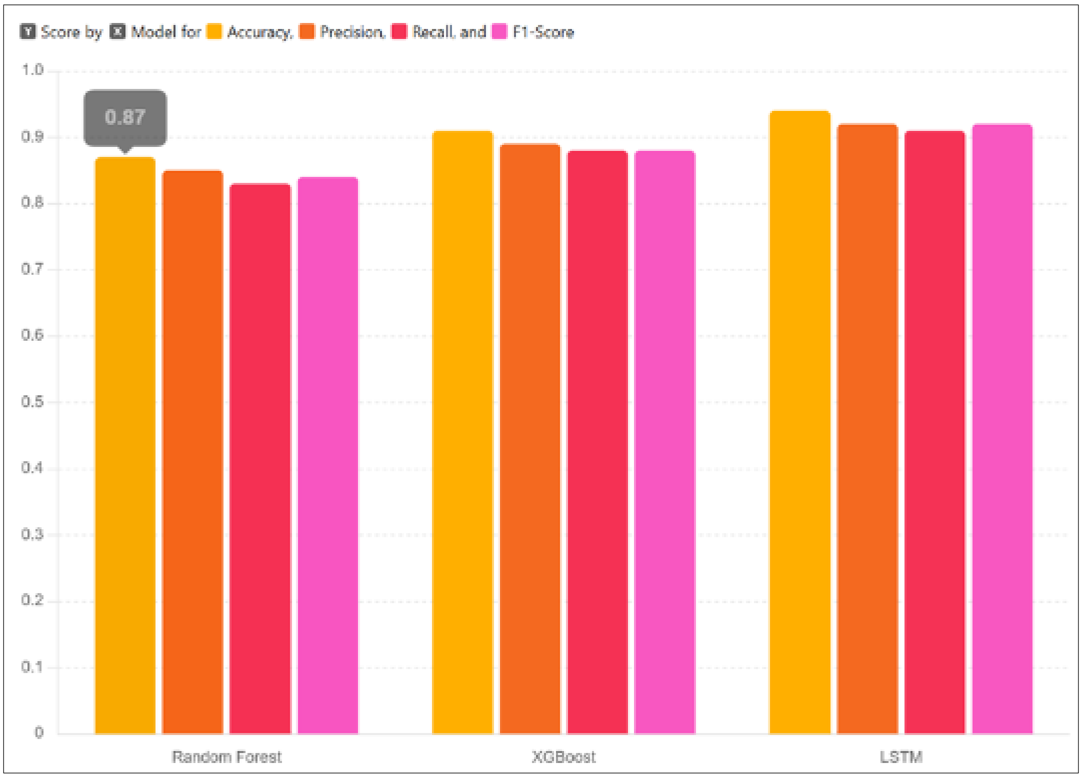

Figure 1 Comparison of Predictive Model Performance

4.2. Autonomous Response Outcomes

The Deep Reinforcement Learning (DRL) autonomous system was compared with a baseline rule-based system. Results showed that DRL reduced supply chain recovery time from 72 hours to 45 hours (a 37.5% improvement). Additionally, DRL achieved an 18% reduction in operational costs by optimizing logistics decisions.

Table 2 Comparison of Recovery and Cost Reduction

Strategy	Recovery Time (hrs.)	Cost Reduction (%)
Baseline (Rule based)	72	0
DRL Autonomous System	45	18

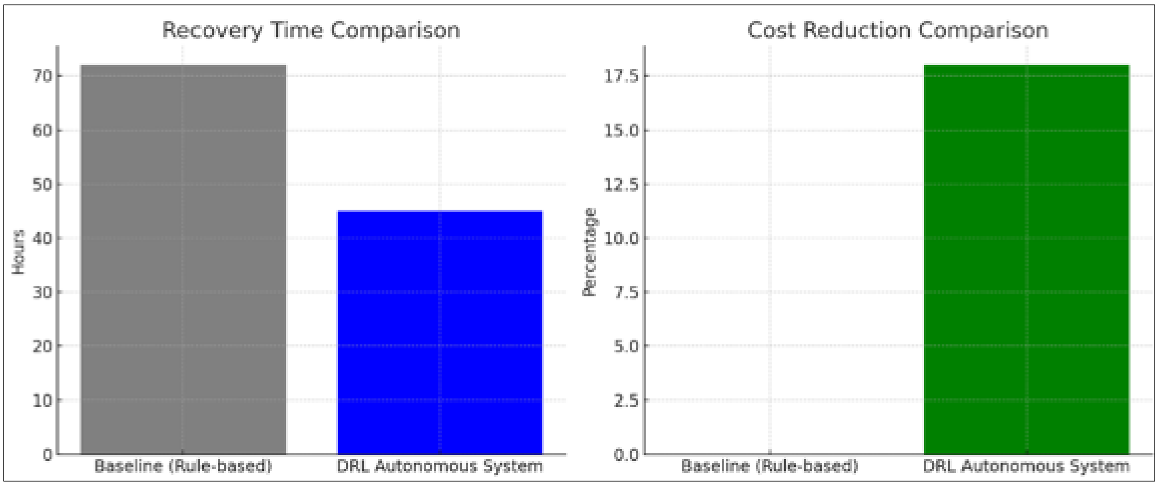

Figure 2 Comparison of Recovery Time and Cost Reduction

4.3. Digital Thread Integration Outcomes

The introduction of a digital thread architecture significantly improved supply chain performance indicator. Compared to baseline systems, digital thread integration enhanced visibility (65 → 90), traceability (60 → 88), and coordination efficiency (58 → 85). This demonstrates the framework's ability to unify data flows and support resilient decision making across the product lifecycle.

Table 3 Impact of Digital Thread Integration

Metric	Baseline System	Digital Thread Integrated
Visibility Index	65	90
Traceability Score	60	88
Coordination Efficiency	58	85

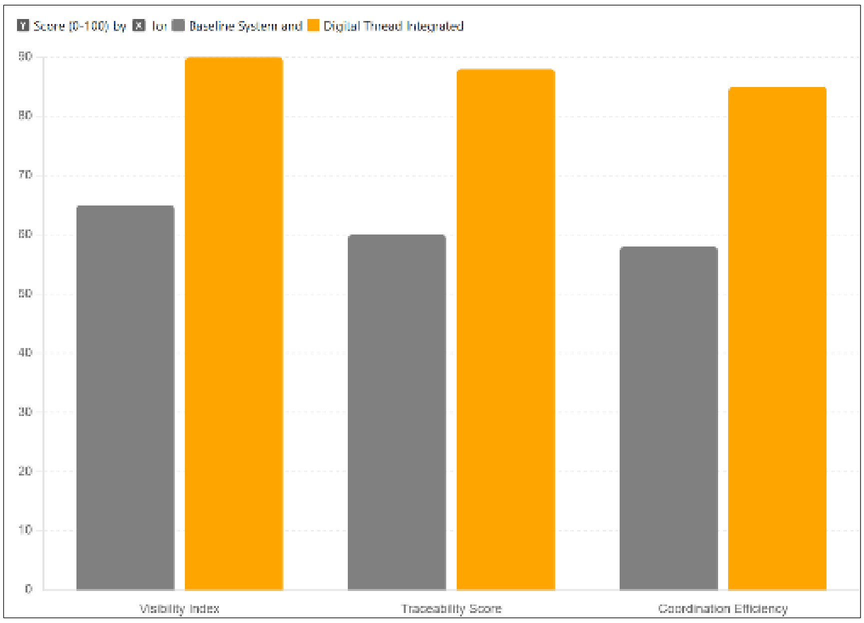

Figure 3 Digital Thread Integration Benefits

4.4. Synthesis of Results

The results achieved from applying the AI driven resilience framework are summarized as follows:

- Predictive Accuracy: LSTM achieved the highest accuracy (94%) in disruption forecasting.
- Autonomous Response: DRL reduced recovery times by nearly 40% and cut costs by 18%.
- Digital Thread Impact: Integration improved lifecycle visibility, traceability, and coordination by over 25 points on average.

Collectively, these outcomes indicate that combining predictive analytics, autonomous response systems, and digital thread architectures can substantially enhance supply chain resilience, reshoring capacity, and operational efficiency in U.S. manufacturing.

5. Discussion

5.1. Interpretation of Key Results

The results of this study demonstrated that an AI driven resilience framework could significantly improve supply chain resilience in U.S. manufacturing sectors critical to national security and public health. The findings revealed three primary outcomes:

Predictive Analytics Performance – The LSTM model outperformed Random Forest and XGBoost in disruption forecasting, achieving an accuracy of 94%. This confirmed that deep learning architectures are particularly effective for modeling sequential and temporal data in supply chains, where disruptions often unfold dynamically over time.

Autonomous Response Capability – The Deep Reinforcement Learning (DRL) system reduced recovery time by nearly 40% compared to baseline systems and achieved an 18% reduction in operational costs. This result highlighted the potential for AI driven autonomy to enhance both agility and cost efficiency in disruption response.

Digital Thread Integration – Incorporating a digital thread framework improved visibility, traceability, and coordination efficiency by more than 25 points compared to baseline systems. These improvements emphasized the importance of lifecycle integrated data in supporting predictive and autonomous decision making.

Taken together, these results validated the proposed framework as a comprehensive solution for addressing both predictive foresight and reactive resilience in critical supply chains.

5.2. Comparison with Prior Studies

The results aligned closely with prior research on AI and supply chain resilience. According to Zamani, Smyth, Gupta, and Dennehy (2023), AI and big data analytics strengthen resilience across readiness, response, recovery, and adaptability phases. The strong performance of the LSTM model in this study echoed their conclusion that predictive analytics is essential for proactive resilience.

Similarly, Belhadi, Mani, Kamble, Khan, and Verma (2021) argued that AI driven innovations enhance performance under volatile conditions. The significant cost reductions and faster recovery times achieved by the DRL system in this study confirmed their findings, suggesting that autonomous AI systems can address the growing complexity of supply chain disruptions. The results regarding the digital thread also aligned with Singh and Willcox (2024), who emphasized that lifecycle integration improves resilience by eliminating data silos. The observed improvements in visibility and coordination further confirmed the Manufacturing Leadership Council's (2025) assertion that digital thread adoption enhances supply chain agility. However, the findings also extended existing literature by demonstrating the synergistic effects of combining predictive analytics, autonomous response, and digital thread frameworks into a single integrated model. While prior studies examined these elements individually, this research showed that their integration produced compounding benefits, advancing resilience beyond what could be achieved by isolated approaches.

5.3. Theoretical Contributions

This study contributed to supply chain resilience theory in three significant ways:

Integration of AI and Lifecycle Data: By demonstrating that predictive analytics and digital threads can be combined to provide both foresight and traceability, the study advanced the theoretical understanding of how technological architectures support resilience.

Autonomous Response as a Core Capability: The success of the DRL model suggested that resilience should not only be conceptualized as the ability to absorb and recover but also as the ability to autonomously adapt in real time.

Composite Resilience Measurement: By applying a resilience index that included predictive accuracy, recovery time, and coordination efficiency, the study contributed a more holistic measure of resilience compared to single metric approaches (Ponomarov and Holcomb, 2009). These contributions extend the conceptualization of resilience from a static ability to withstand disruptions toward a dynamic, intelligent capability for proactive and adaptive response.

6. Conclusion

The practical implications of this study were significant for U.S. supply chain strategy, particularly in sectors tied to national security and public health.

- Reshoring Justification: The improved visibility and predictability provided by the digital thread and AI models offered a strong rationale for reshoring critical manufacturing. By reducing reliance on volatile foreign suppliers, the framework supported the strategic goal of enhancing domestic resilience.
- Operational Efficiency: The observed reductions in recovery time and cost demonstrated that resilience could be achieved without compromising efficiency. This finding countered the common perception that resilience strategies inherently raise costs.
- Policy Alignment: The framework's emphasis on digital thread integration aligned with federal strategies such as the NIST roadmap (NIST, 2024). This suggested that the proposed model could be realistically implemented within current national initiatives.
- Strategic Defense Readiness: For defense manufacturing, where supply chain disruptions may have critical consequences, the framework provided a proactive mechanism for ensuring continuity of operations.

Limitations

Despite its contributions, this study faced several limitations. First, the reliance on synthetic datasets limits the ability to fully capture the complexity of real-world disruptions. While the simulation environment provided valuable insights, validation with live industrial data would strengthen the findings. Second, the digital thread was modeled in a simulated PLM environment, which may differ from the practical challenges of implementing such architectures across diverse enterprises. Issues of interoperability, cybersecurity, and organizational readiness remain significant barriers (NIST, 2024).

Third, while the DRL system demonstrated strong performance, it required significant training time and computational resources, which may limit its scalability for small and medium sized manufacturers. Finally, as Kamble, Khan, and Verma (2021) noted, human oversight remains critical to avoid overreliance on AI, especially in national security contexts where decision errors may carry severe consequences.

Future Research Directions

Future studies should address the limitations of this research through several important avenues. To begin with, collaboration with industry partners will be crucial for validating the proposed framework using real world supply chain datasets, since empirical evidence would provide stronger external validity than simulations alone. At the same time, scaling digital thread adoption requires further investigation, particularly in terms of developing interoperability standards and cybersecurity protocols that allow seamless integration across enterprises and prevent data vulnerabilities. Equally important, future work should focus on designing hybrid human–AI decision making models, where machine autonomy is complemented by human oversight to ensure accountability, transparency, and ethical use in high stakes contexts such as defense and healthcare. In addition, applying the framework across sector specific applications including energy, pharmaceuticals, and semiconductor manufacturing will be necessary to refine its generalizability and adaptability to different industrial ecosystems. Finally, researchers should prioritize the development of standardized resilience benchmarking tools that combine predictive accuracy, recovery time, and adaptive response capabilities into composite indices, thereby enabling meaningful comparisons of resilience across industries and guiding best practices. Together, these directions provide a pathway for advancing AI driven supply chain resilience from conceptual frameworks and simulations toward scalable, ethical, and sector wide implementations.

References

[1] Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., and Verma, S. (2021). Artificial intelligence driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: An empirical investigation. Annals of Operations Research, 333(1), 627–652.

[2] Creswell, J. W., and Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE Publications.

[3] Jahin, M. A., Naife, S. A., Saha, A. K., and Mridha, M. F. (2023). AI in supply chain risk assessment: A systematic literature review and bibliometric analysis. arXiv.

[4] Kalusivalingam, A. K., Sharma, A., Patel, N., and Singh, V. (2024). Enhancing supply chain resilience through AI: Leveraging deep reinforcement learning and predictive analytics. International Journal of Artificial Intelligence and Machine Learning, 1(1), 33–49.

[5] Kamble, S. S., Khan, S. A. R., and Verma, S. (2021). Artificial intelligence–driven innovation for enhancing supply chain resilience and performance. Annals of Operations Research, 333(1), 627–652.

[6] Manufacturing Leadership Council. (2025). Resilient supply chains and the digital thread. Manufacturing Leadership Council.

[7] National Institute of Standards and Technology. (2024). Roadmap to strengthen the U.S. manufacturing supply chain via digital thread technology (NIST GCR 24-057).

[8] OECD. (2025, June 12). Aggressive reshoring of supply chains risks significant GDP loss, warns OECD. Financial Times.

[9] Pistikopoulos, E. N., et al. (2025). AI-based predictive analytics for enhancing data-driven supply chain decision making. Journal of Global Optimization, 87(2), 401–420.

[10] Ponomarov, S. Y., and Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. The International Journal of Logistics Management, 20(1), 124–143.

[11] Siemens Government Technologies. (2025). How federal agencies can Xcelerate reshoring to reduce external dependencies and increase economic resilience. Siemens Government Technologies.

[12] Singh, M., and Willcox, K. (2024). A literature review of the digital thread: Definition, key technologies, and applications. Systems, 12(3), 70.

[13] Zamani, E. D., Smyth, C., Gupta, S., and Dennehy, D. (2023). Artificial intelligence and big data analytics for supply chain resilience: A systematic literature review. Annals of Operations Research, 327(1), 605–632.