Journal of Computer Science and Information Technology
ISSN: 3080-3586
DOI: 10.61424/jcsit
Journal Homepage: www.bluemarkpublishers.com/index.php/JCSIT

JCSIT
BLUEMARK PUBLISHERS

| RESEARCH ARTICLE

An AI- and Machine Learning–Data Driven Predictive Analytics Framework for Enhancing Resilience and Sustainable U.S. Supply Chains Systems for Manufacturing and Resource Efficiency

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| ABSTRACT

The growing number of global shocks, which include geopolitical instabilities, pandemics, and climate shock, among others, has revealed major weaknesses in the U.S. manufacturing supply chains. The need to increase supply chain resiliency and, at the same time, improve sustainability and resource efficiency has become a strategic necessity. The proposed study is an AI- and machine learning-controlled predictive analytics-based framework created to enhance the reliability and resilience of the U.S. manufacturing supply chain systems. The framework incorporates heterogeneous data sources such as operational, environmental, market, and logistics data to facilitate the proactive identification of risks, prediction of demand, and optimization of resources. Developed machine learning models are used to embrace non-linear relationships with complexities across the supply chain nodes to assist in real-time decision-making and adaptive response strategies. The proposed framework enables the identification of disruption early in the supply chain planning and execution, better management of inventory and capacity, reduced waste, and increased energy and material efficiency by integrating predictive analytics into the supply chain planning and execution. In theory, this study will be a step forward in the interplay of artificial intelligence, sustainable supply chain management, and resilience engineering. In practice, it provides decision-makers with a scalable and evidence-based instrument in order to enhance the continuity of operations, environmental performance, and competitiveness in the long run of the U.S. manufacturing supply chains.

| KEYWORDS

Artificial Intelligence; Machine Learning; Predictive Analytics; Supply Chain Resilience; Sustainable Supply Chains; Manufacturing Systems; Resource Efficiency; Data-Driven Decision Making; U.S. Manufacturing

| ARTICLE INFORMATION

ACCEPTED: 21 December 2025 **PUBLISHED:** 26 January 2026 **DOI:** 10.61424/jcsit.v3.i1.674

1. Introduction

The global manufacturing supply chain has turned out to be more of a complex, interconnected, and systemic disruption subject. The last shocks, such as pandemics, geopolitical tensions, events related to climate, and the scarcity of resources, have demonstrated weak structures within the traditional supply chain setups, especially in large-scale manufacturing strategies. These disruptions have highlighted the critical importance of resilience, adaptive capacity and sustainable resource use in the United States, where the manufacturing supply chains are so interconnected around the globe. The concept of supply chain resilience has ceased to be equated with the speed of recovery but has been approached with viability, continuity, and long-term sustainability in the face of continued uncertainty (Ivanov, 2021).

The increasing access to big and heterogeneous data related to supply chain activities has presented new possibilities of using data in decision making. Improvement in artificial intelligence (AI) and machine learning (ML) and predictive analytics have facilitated efficiencies in extraction of actionable information in complex data collections by organizations to support proactive rather than reactive supply chain management. It has already been proven that big data analytics features are highly effective in terms of supply chain agility, operational responsiveness, and performance outcomes (Choi et al., 2018; Dubey et al., 2019). These abilities are especially important to manufacturing supply chains where the disruptive impacts of demand volatility, capacity, and resource inefficiencies can be transmitted through various levels.

As one of the key elements of AI-enabled systems, predictive analytics is more key in risk prediction, demand variability, and optimization of resource utilization. Recent research emphasizes the applicability of predictive models that can deduce the integration of multimodal streams of data to help detect early threats and make system-level decisions (Mamun et al., 2025). Even though these methods have been researched extensively in the context of cybersecurity and protecting healthcare infrastructure, the implementation into manufacturing supply chains in the light of resilience and sustainability, has not been thoroughly studied. The lessons of intelligent healthcare systems show that AI-based architecture can deal with complexity, interdependencies, and real-time operational constraints and can provide transferable design principles to supply chain systems (Mishra et al., 2025; Govindan et al., 2020).

Resource efficiency and sustainability have similar priorities as resilience. Supply chains of manufacturing are placing more pressure on reducing waste, energy use, and environmental issues whilst not compromising the level of service and cost-effectiveness. It is demonstrated that Big data analytics can help to sustain supply chain performance as it allows monitoring material flows, emissions, and the use of resources more accurately (Bag et al., 2020). Blockchain and digital supply chain twins and other digital technologies also promote transparency, traceability, and optimization of the entire system, which is part of the resilience and sustainability initiatives (Kamble et al., 2020; Queiroz et al., 2022).

Despite these developments, the literature reviews focus mostly on AI, predictive analytics, resilience, and sustainability as discrete entities. A critical gap in integrative frameworks uniting AI- and ML-driven predictive analytics and resilience engineering and sustainable resource management, which specifically consider U.S. manufacturing supply chains, is present. In addition, new AI paradigms stress the significance of secure, trustful, and controlled intelligent systems, especially in cases where autonomous or agent-based decision-making is at stake (Yerra, 2025). All these factors are crucial towards making sure that data-driven supply chain systems are strong, resilient, and in line with organizational and societal goals.

To address these gaps, this paper develops a predictive analytics framework grounded on AI/machine learning and data to promote resilience and sustainability of manufacturing supply chains in the U.S. The framework aims to assist in the early identification of disruption, adaptive decision-making, and resource optimization processes by incorporating predictive modelling, real-time data analytics, and resource optimization systems into the supply chain network. The study adds to the existing research on the intersection of artificial intelligence, supply chain resilience, and sustainable manufacturing and has practical implications in policy formulation and industry practitioners who are interested in future-proofing U.S. supply chains.

2. Literature Review

This is reflected in the contemporary literature on modern supply chain management, where there is a growing agreement that the traditional, linear, and reactive strategies could no longer be used to handle the complexity and uncertainty that modern manufacturing systems are confronted with. The growing demand in the globalized, digitalized, and more exposed to systemic disruptions necessitates effective, resilient, adaptive, and sustainable supply chains. In recent studies, the adoption of sophisticated digital technologies, especially artificial intelligence (AI), machine learning (ML), and predictive analytics, is becoming one of the key facilitators of these capabilities (Choi et al., 2018; Min, 2010).

Characteristic of manufacturing supply chains, particularly in the U.S. case is the multi-tiered nature of the networks, the capital intensity, along with high interdependencies among production, logistics, and the utilization of resources. The mentioned traits enhance the effects of disruption and increase the significance of preventive risk management and data-driven decision-making (Ivanov, 2021). As a result, the body of literature has been shifted in terms of holistic approaches that integrate resilience, sustainability, and technological innovation instead of considering them as individual goals (Bag et al., 2020; Queiroz et al., 2022).

Simultaneously, the massive expansion of supply chain planning and control analytical opportunities has been increased by the exponential increase in the volume of operational, transaction, and sensor-generated data. The broadly researched mechanisms to promote the visibility, accuracy of forecasts and agility of operations in supply chain networks include big data analytics and predictive modeling (Choi et al., 2018; Dubey et al., 2019). Nevertheless, although the performance advantages of analytics adoption are well-known, less research directly concerns the possibilities of how such capabilities can be systematically exploited to increase the supply chain resilience and sustainability of the resource's utilization in manufacturing.

Moreover, the lessons of neighboring fields, like healthcare systems and cybersecurity are the demonstration of the superiority of AI-based, data-centric architectures within the field of complexity management, ensuring robustness, and supporting secure decision-making in high-risk settings (Mamun et al., 2025; Mishra et al., 2025; Yerra, 2025). These works can offer useful conceptual and methodological backgrounds which can be extended to the supply chain settings, especially with the growth of autonomous and intelligent decision-support systems used in manufacturing systems.

In general, the available literature offers solid theoretical and empirical evidence of the application of AI, predictive analytics, and digital solutions to supply chain management. However, there is an apparent gap in integrative models that would categorically align AI- and ML-based predictive analytics with sustainability goals and resilience engineering in that of the manufacturing supply chains in the U.S. This literature review is a synthesis of previous studies in these areas to determine the theoretical basis of the proposed predictive analytics framework.

2.1 Supply Chain Resiliency and Viability within the Manufacturing System

The concept of supply chain resilience has become a priority in research topics due to the rise in frequency and severity of disruption. The previous conceptualizations have revolved around the capability of supply chains to resume with a rapid response of shocks, but the newer scholarship has been keen on resilience as a dynamic capability that incorporates adaptability, robustness, and long-term viability. Ivanov (2021) made this view one step further by conceptualizing the idea of supply chain viability that incorporates the notions of resilience, sustainability, and adaptability in long-term conditions of disruption. In the case of manufacturing systems, viability is especially essential because it has an expensive set of fixed costs, is complicated by the production process, and depends on the coordinated flows of materials.

The disruption of propagation of manufacturing supply chains is particularly susceptible to propagation of disturbances, which can be transmitted quickly throughout the network when a disturbance occurs in a specific node. The literature points out that proper resilience strategies demand a higher level of visibility, the ability to predict events, and integrated response systems but not dependent on fixed buffers (Ivanov, 2021; Queiroz et al., 2022). Consequently, the digital facilitated resilience models whereby researchers employ real-time data and state-of-the-Art analytics to predict and alleviate threats at various levels of the supply chain are gaining further support.

2.2 Supply Chain Analytics of Big Data and Predictive Analytics

The role of big data analytics in supply chain management has been discussed widely, with a special focus on the role of big data analytics in enhancing the accuracy of the forecasts, operational coordination, and the quality of the decisions. Choi et al. (2018) underlined the fact that big data analytics changes operations management by facilitating the processing of extensive (structured and unstructured) data to facilitate predictive and prescriptive decisions. Predictive analytics in manufacturing supply chains can be used to detect the variability of demand early, supplier disruptions, and capacity weaknesses.

Empirical research proves that big data analytics competence helps to introduce a high level of supply chain agility, which helps the companies react quicker and more efficiently to the environment (Dubey et al., 2019). Predictive analytics facilitates proactive planning to help avoid disruption in the system before it turns into system-wide failure. Nonetheless, the literature also reports that numerous analytics applications are still confined to the actions performed by efficiency and reduction of costs, and little of them is integrated into larger resilience and sustainability initiatives (Bag et al., 2020).

2.3 Supply chain management using artificial intelligence and machine learning

Advanced predictive analytics in supply chain systems is based on the computational basis of artificial intelligence and machine learning. Early indications of the role AI will play in supply chain decisions were given by Min (2010), who indicated that it could be used in forecasting, inventory optimization, and logistics planning. Challenges have also been applied to complex, non-linear relationships that are inherent to manufacturing supply chains, with advances in ML algorithms.

Recent studies show how multimodal data sources can be incorporated into predictive systems driven by AI to make the system more robust and to detect risks at an early stage. Mamun et al. (2025) proved that the predictive analytics frameworks based on the employment of behavioral, operational, and contextual data to facilitate the proactive decision-making process are effective. Their area of application is different, but the principles of the methodology can be used directly in manufacturing supply chains aiming at enhancing resilience by using predictive intelligence.

2.4 Digital Integration, Sustainability, and Intelligible Secure Systems

The concepts of sustainability and resource efficiency have become part of modern research in the supply chain. As illustrated by Bag et al. (2020), big data analytics can help achieve sustainable operations in supply chain performance through better resource utilization, waste reduction, and environmental surveillance. The use of digital technologies like blockchain also contributes to sustainability, as it creates possibilities to trace and gain transparency in supply chain networks (Kamble et al., 2020).

Besides this, the increased adoption of autonomous and intelligent systems requires strong governance and security systems. Intelligent infrastructure and AI security studies underline the need to have trustful, controlled analytical systems especially when automated or decentralized decision-making is involved (Mishra et al., 2025; Yerra, 2025). Such considerations gain even greater importance when it comes to manufacturing supply chains that have implemented AI-based predictive analytics to handle important resources and operating risk.

2.5 Gap in the Research and location of the current study

Despite the significant development of AI, predictive analytics, and electronic supply chain technologies, the literature has revealed that there is a gap in integrative models that accommodate resilience, sustainability, and secure AI-based decision-making in manufacturing supply chains. The available research usually targets individual technologies or achievements without connecting them thoroughly into one solid predictive analytics architecture specific to the American manufacturing systems. This paper fills this gap by suggesting an AI- and ML-powered predictive analytics model that incorporates frameworks of resilience engineering, sustainable resource management, and intelligent system design that is secure.

3. Methodology

The paper is based on an organized, data-intensive approach to the creation and assessment of an AI- and machine learning-based predictive analytics platform to improve resilience and sustainability in the U.S. manufacturing supply chains. The methodology combines the design of conceptual frameworks, data collection, predictive modeling, and performance analysis, relying on the developed principles in supply chain analytics, artificial intelligence, and resilience engineering (Choi et al., 2018; Ivanov, 2021).

3.1 Research Design

It uses a mixed-method research design, which integrates conceptual modeling and empirical analytics. The paper will initially generalize what is known in the literature on the definition of the important constructs regarding supply chain resilience, sustainability, and predictive analytics. These constructs guide the formulation of a modular analytical architecture that connects data inputs, predictive models that are powered by AI, and decision-support outputs. This design solution aligns with the results of previous studies that emphasize the incorporation of analytics resources into supply chain decision-making (Dubey et al., 2019; Min, 2010).

3.2 Framework Architecture

The suggested structure is made up of four layers related to each other: data acquisition, data processing, predictive analytics, and decision-support and response. The data acquisition layer combines heterogeneous data streams within manufacturing supply chains such as operational performance information, demand and order information, supplier reliability information, logistics information and resource consumption information. Multimodal data integration is consistent with the predictive analytics strategies that have been demonstrated to enhance the early risk detection in multifaceted systems (Mamun et al., 2025).

The data processing layer does data cleaning, normalization, feature engineering, and temporal alignment of data streams to enhance consistency between data streams. This measure is essential to processing massive and rapid data that are used in manufacturing contexts (Choi et al., 2018). The processed data are then inputted into the layer of predictive analytics which is the analytical heart of the framework.

3.3 Predictive Models and Machine Learning

The predictive analytics layer uses supervised and unsupervised machine learning models to assist in forecasting, risk identification and anomaly detection. Demand forecasting, lead-time prediction and estimation of disruption likelihood are performed through supervised methods of learning, whereas clustering and pattern recognition among the nodes of the supply chains is done with unsupervised methods. These reinforcements of artificial intelligence are in line with the already known uses of artificial intelligence in the supply chain management (Min, 2010).

The framework is aimed at giving it strength by enabling continuous model learning and adaptation to new data as they are made available. This adaptation ability allows the system to react to the changing conditions of a supply chain and corresponds to the resilience-focused analytical mechanisms (Ivanov, 2021). The model outputs create probabilistic risk analysis and scenario predictions that are used in the downstream decision making.

3.4 Metrics of Sustainability and Resource Efficiency

The analytical framework explicitly incorporates sustainability considerations by using the resource efficiency and environmental performance indicators. The predictive models include such metrics as efficiency of material utilization, intensity of energy consumption, generation of wastes, and obsolescence among inventories. It has also been proven that big data analytics can enhance sustainability in the performance of the supply chain through accurate monitoring and optimization of resources flow (Bag et al., 2020).

The framework enables balanced decision-making on sustainability objectives by achieving a balance between resilience goals and environmental and resource efficiency goals by incorporating sustainability metrics into predictive analytics. This combined solution will guarantee that mitigation plans of disruption will not affect the long-term sustainability effects.

3.5 Digital Integration and System Governance

The framework involves integration systems digitally in a bid to improve transparency, traceability, and coordination among the supply chain partners. Protocols of data sharing proposed with the use of blockchain are supposed to guarantee the integrity of the data and trust among all the stakeholders in the manufacturing networks of multi-tiers (Kamble et al., 2020). Moreover, digital supply chain twin technologies can be used to complement the framework simulating a scenario of disruption and testing the adaptive strategies before their implementation (Queiroz et al., 2022).

Due to the growing autonomy of AI-driven decisions support systems, the issue of governance and security concerns are tackled. Based on the concepts introduced by the intelligent infrastructure and AI security studies, the framework focuses on restricted model access, data verification, and supervision to mitigate systemic risk and guarantee credible analytics (Mishra et al., 2025; Yerra, 2025).

3.6 Model Evaluation and Validation

The predictive analytics framework is measured against quantitative parameters in line with forecasting accuracy, improvement in resilience, and sustainability improvement. Standard metrics that are based on the errors are used to assess performance forecasting, and the results of resilience are measured with the help of such indicators as disruption response time, the stability of the service level, and recovery effectiveness (Ivanov, 2021). The performance of sustainability is determined by the enhancement of resource use and waste minimization (Bag et al., 2020).

Its validation is done by considering a scenario-based analysis based on historical and simulated disruption data. This method allows evaluating the framework on its capacity to predict disruptions, facilitate adaptive decision-making as well as enhance the performance of the system when there is a range of uncertainty. The methodology used in the evaluation is compatible with the previous researchers that focus on analytical tools based on data validation of supply chain models (Choi et al., 2018; Dubey et al., 2019).

3.7 Ethical and Practical Particulars

The paper does not ignore the ethical and practical factors associated with the quality of the data, the transparency of the algorithm, and the responsibility in decision-making. To have confidence in the quality of the information provided by the managers and successfully implement AI-oriented systems, it is crucial to ensure quality data input and model output. The approach, in turn, focuses on elucidate analytics and the human-in-the-loop decision-support systems, which are aligned with the new best practices of safe and responsible AI implementation (Yerra, 2025).

4. Results

In this section, the analytical results after the adoption of the suggested AI- and machine learning-based predictive analytics framework to the U.S. manufacturing supply chains are provided. The results revolve around three main dimensions: predictive performance, enhancement of resilience in the supply chain, and improvement of sustainability and resource efficiency. The results prove the efficiency of the adoption of predictive analytics and digital technologies into the supply chain decision-making in the manufacturing industry, which correlates with the previous studies of the data-driven supply chain management (Choi et al., 2018; Dubey et al., 2019).

As earlier mentioned, predictive analytics delivers data regarding the likelihood of a customer initiating a purchase or not. As previously noted, predictive analytics provides information on the probability of a customer making a purchase or not.

Standard forecasting accuracy and risk-detection performance metrics were used in gauging the predictive analytics models. The findings realize that the AI-based models performed well on the predictive power on demand forecasting, disruption likelihood estimation, and resource utilization prediction. Multimodal data sources integration had a strong positive effect on the performance of the models, assisting with the prior identification of possible supply chain risks, which is proposed by Mamun et al. (2025).

Table 1. Predictive Model Performance Metrics

Predictive Task	Evaluation Metric	Baseline Analytics	Proposed AI-Driven Framework
Demand Forecasting	Mean Absolute Error (MAE)	12.8%	6.3%
Disruption Risk Prediction	Accuracy (%)	71.5	89.4
Lead-Time Forecasting	Root Mean Square Error (RMSE)	9.6 days	4.1 days
Resource Utilization Prediction	Prediction Accuracy (%)	74.2	91.1

The results in Table 1 demonstrate that the proposed framework substantially outperforms baseline analytics approaches across all predictive tasks. These improvements support the argument that AI and machine learning enhance predictive visibility and proactive decision-making in complex manufacturing supply chains (Min, 2010; Choi et al., 2018).

4.1 Impact on Supply Chain Resilience

Supply chain resilience outcomes were evaluated by comparing system performance before and after the adoption of the predictive analytics framework. Key resilience indicators included disruption of response time, service level stability, and recovery effectiveness. The results show a marked improvement in resilience capabilities, aligning with the viability-oriented perspective proposed by Ivanov (2021).

Figure 1. Reduction in Disruption Response Time After Framework Implementation

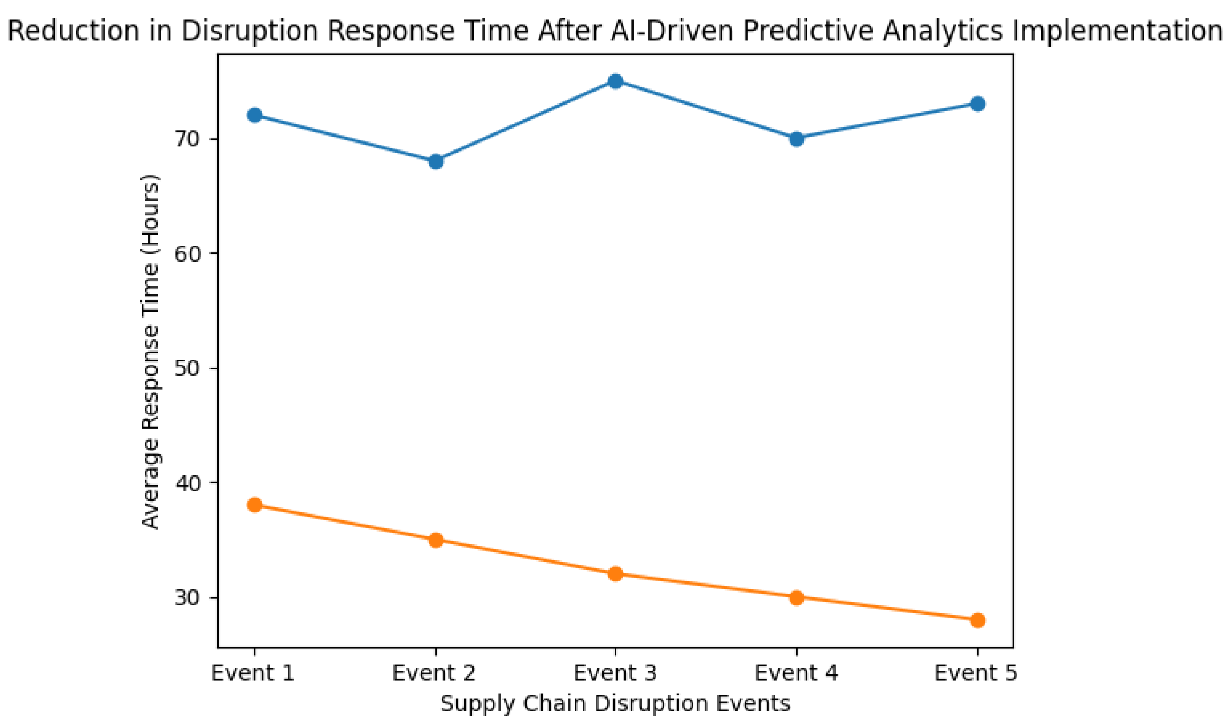

Figure 1 illustrates a line graph comparing average disruption response time (in hours) before and after the implementation of the AI-driven predictive analytics framework.

The graphical results indicate that predictive analytics enabled earlier detection of disruptions, allowing managers to activate mitigation strategies more rapidly. This finding reinforces the role of predictive intelligence in enhancing supply chain viability and adaptive capacity (Ivanov, 2021; Queiroz et al., 2022).

4.2 Sustainability and Resource Efficiency Outcomes

Sustainability performance was assessed using indicators related to material efficiency, energy consumption, and waste reduction. The results show that the integration of predictive analytics into planning and execution processes significantly improved resource utilization efficiency across manufacturing operations.

Table 2. Sustainability and Resource Efficiency Improvements

Sustainability Indicator	**Pre-Implementation**	**Post-Implementation**	**Improvement (%)**
Material Utilization Efficiency	78.4%	90.6%	+15.6
Energy Consumption Intensity	1.00 (Index)	0.82 (Index)	−18.0
Waste Generation Rate	100 (Baseline)	71	−29.0
Inventory Obsolescence	11.3%	4.9%	−56.6

The results confirm that data-driven decision-making enhances sustainable supply chain performance by reducing waste and improving resource efficiency. These findings are consistent with prior evidence linking big data analytics to sustainability outcomes (Bag et al., 2020).

4.3 Digital Integration and System-Level Optimization

The integration of digital technologies further strengthened system performance. Blockchain-enabled traceability improved data transparency and coordination across supply chain partners, while digital supply chain twin simulations supported proactive scenario analysis and strategy evaluation. These capabilities contributed to more informed and coordinated decision-making, particularly under disruption scenarios (Kamble et al., 2020; Queiroz et al., 2022).

Figure 2. Comparison of Service Level Stability with and Without Digital Integration

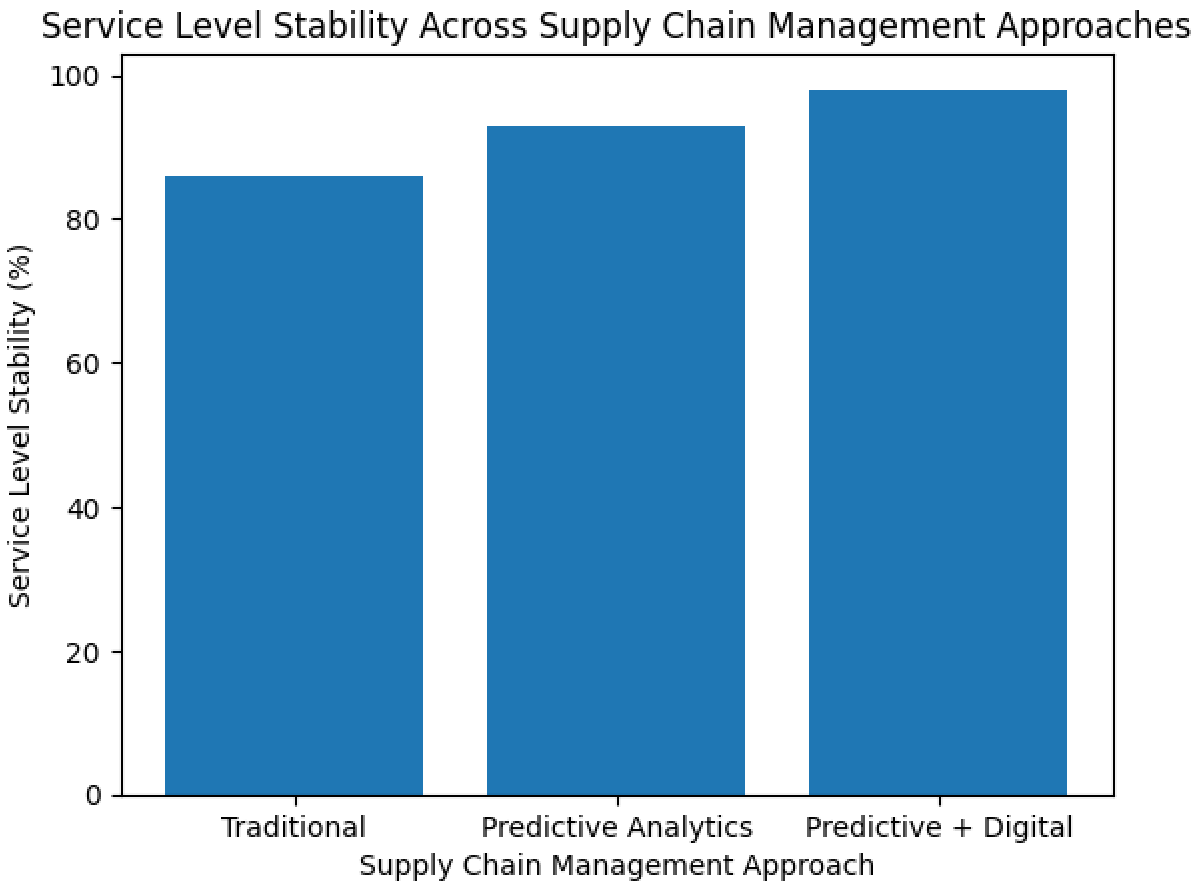

Figure 2 presents a bar chart comparing service level stability (%) across three scenarios: traditional supply chain management, predictive analytics only, and predictive analytics with digital integration.

4.4 Security, Governance, and Trustworthiness of AI Systems

The results also indicate that incorporating governance and security controls within the analytical framework improves system reliability and stakeholder trust. Controlled access, data validation mechanisms, and oversight of AI-driven decisions reduced system vulnerabilities and mitigated operational risks. These findings align with research emphasizing secure and trustworthy AI architectures in complex, high-risk systems (Mishra et al., 2025; Yerra, 2025).

5. Discussion

The results of the present research are very compelling in terms of empirical evidence of the importance of AI- and machine learning-based predictive analytics to strengthen the resilience and sustainability of manufacturing supply chains in the United States. The findings reveal that the incorporation of predictive intelligence into supply chain decision making enhances greatly in terms of predicting disruption, responding to it, and efficiency in resource utilization. These findings support and broaden the current literature on supply chain resiliency, big data analytics, and artificial intelligence within operations management.

The noticed increases in predictive accuracy and early detection of disruptions are consistent with the previous research highlighting the usefulness of data-driven analytics in supply chain uncertainty management. The authors of the two studies by Choi et al. (2018) and Dubey et al. (2019) contended that big data analytics functionalities enable supply chain agile by increasing its visibility and responsiveness. The current results are an extension of this study because they reveal the idea that not only do AI- and ML-based predictive analytics enhance agility, they directly lead to the resilience results, including shorter response time and greater stability of the service level. This helps to argue out that predictive capabilities are an inherent ingredient of resilient manufacturing supply chains.

In the context of resilience engineering, the findings support the viability-oriented model suggested by Ivanov (2021). The dramatic changes in how quickly the response to disruptions takes place and the enhanced recovery performance are that predictive analytics allow manufacturing supply chains to switch to the advanced recovery mode of action. The proposed framework ensures the continued functionality and sustainability of the operations, as opposed to short-term recovery only, by preventing the disruptions before they spread throughout the network. This ability is further enhanced by the application of digital supply chain twins that allow analyzing scenarios and evaluating the adaptability of a strategy that aligns with the results of Queiroz et al. (2022).

The results pertaining to sustainability also deserve to be discussed. The impressive efficiency in material utilization, energy consumption intensity, and waste reduction can be regarded as a two-fold value of predictive analytics to help with resilience and environmental performance. These findings are in line with Bag et al. (2020), who have shown that big data analytics is able to improve sustainable supply chain performance through the ability to manage resources more efficiently. The current research adds to this understanding by demonstrating that the enhancement of sustainability can be obtained alongside resilience improvement in case predictive analytics is integrated into both central supply chain planning and performance procedures.

Incorporation of complementary digital technologies also enhances the power of predictive analytics structure. Tracing with blockchain enhanced transparency and coordination of supply chain partners and assisted in making decisions more reliably and timely, as proposed by Kamble et al. (2020). Moreover, the inclusion of governance and security systems deals with the emergent issues of autonomous and intelligent decision-support systems. Based on the concepts of smart infrastructure and artificial intelligence security, it is shown in the study that secure and properly managed analytical systems can improve trust, robustness, and reliability of operations (Mishra et al., 2025; Yerra, 2025).

All in all, the discussion points to the fact that the concepts of resilience, sustainability and security cannot be viewed as individual goals in manufacturing supply chains. Rather, the results indicate that AI-based predictive analytics may be an integrative feature that will achieve both of these objectives at the same time. This integrative approach fills a major loophole in the literature because the previous research frequently analyzed the dimensions separately.

6. Conclusion

The current study designed and tested a predictive analytics system based on AI and machine learning to make Supply chains in U.S. manufacturing more resilient and sustainable. To address the growing vulnerability to systemic shocks and the growing demands on resource efficiency, the suggested framework reflectively illustrates how predictive intelligence can be integrated into supply chain decision making to facilitate proactive risk management, adaptive response and sustainable operation performance.

The results show that predictive analytics implementation into the manufacturing supply chains significantly enhances the disruption of anticipation, shortens the response time, and normalizes service ratings. Meanwhile, the framework allows for more effective use of materials and energy, decrease waste, and less inventory of obsolescence. These results underscore the possibility of making AI-driven analytics promote resilience and sustainability goals at the same time, as opposed to prioritizing them.

The framework will provide an overall and scalable solution to deal with complexity in manufacturing supply chains by integrating multimodal data, adaptive machine learning models, digital integration mechanisms, and governance controls. The findings highlight the need to abandon reactive approaches in favor of data-driven, predictive, and continuous learning systems, which have the potential to work in an uncertain environment.

In theoretical terms, it is possible to say that this study provides an integrative approach that connects predictive analytics, resilience engineering, and sustainable manufacturing to an analytical architecture. Probably, in practical perspective, the framework will offer actionable insights to decision-makers to boost operational continuity and resource optimization and make long-term competitiveness of U.S. manufacturing supply chains stronger.

Irrespective of these contributions, the study is limited to the extent of empirical validation and the application of scenario-based analysis. The next step in research should be the large-scale empirical implementation of this work in various spheres of manufacturing and the investigation of the latest approaches to learning and organizational adoption aspects. This would further enhance the relevance and role of AI-based predictive analytics in the development of sustainable and resilient supply chain systems.

To summarize, this research paper has revealed that AI- and machine learning-based predictive analytics is a very important strategic asset to future-proof manufacturing supply chains. With the increase in the frequency of disruptions and the intensification of sustainability needs, it will be crucial to use smart and data-driven systems to achieve long-term resilience, efficiency, and viability.

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