AI and Predictive Analytics for Supply Chain Risk Management: Opportunities for U.S. Manufacturing Resilience

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DOI: https://doi.org/10.51583/IJLTEMAS.2026.15020000036

Received: 16 February 2025; Accepted: 21 February 2026; Published: 05 March 2026

ABSTRACT

Recent shocks in the global supply chain such as pandemic related shutdowns and semiconductor shortages have shown the susceptibility of the U.S. manufacturing supply chains. Conventional risk management practices that are mostly based on historical averages and reactive practices have not been effective in unpredictable environments. This paper examines the connection between artificial intelligence (AI) and predictive analytics and reinforcing risk identification, forecasting, and resilience in the U.S. manufacturing industry. We assess the performance of predictive models including ARIMA, Prophet, and Random Forest using the secondary data from U.S. Census Bureau, Bureau of Labor Statistics, and publicly available logistics datasets. The most important measures of resilience are forecast error (MAPE, RMSE), inventory turnover, order fulfillment, and recovery time. The findings indicate that predictive analytics can greatly reduce errors in predictions as well as enhance the outcomes of resilience with the Random Forest being better in terms of reducing forecast error by up to 30% as well as increasing order fulfillment rates by 15% compared to traditional models. A model-derived association analysis using simulation-based performance metrics further indicates statistically significant directional relationships between predictive analytics capability and resilience indicators. These results highlight the value of predictive analytics as an input to operational decision-making. To managers, the study illustrates the use of digital tools to help them get actionable information on the risks of disruption and to policymakers, it is part of wider efforts to strengthen national supply chain resilience. This study can enhance the empirical understanding of AI-facilitated models and introduce feasible resilience metrics.

Index terms: Artificial intelligence, Predictive analytics, Supply chain resilience, Risk management, U.S. manufacturing, Forecast accuracy, Business intelligence.

INTRODUCTION

Supply chains supporting U.S. manufacturing have become increasingly vulnerable to large-scale disruptions caused by pandemics, geopolitical tensions, and critical material shortages. The COVID-19 crisis exposed how quickly global production and distribution networks can break down, particularly in strategically important sectors such as semiconductors, automotive manufacturing, and consumer goods. These disruptions revealed the limitations of traditional, reactive risk management approaches that rely heavily on historical averages rather than forward-looking decision support. As a result, the ability to anticipate disruptions and respond proactively has emerged as both an operational necessity for firms and a strategic priority for U.S. industrial policy.

Recent literature identifies supply chain resilience as a critical capability that enables firms to anticipate, absorb, recover from, and adapt to unexpected shocks. While prior studies emphasize concepts such as agility, redundancy, and flexibility, resilience measurement remains inconsistent across empirical research. Many studies rely on qualitative frameworks or generalized indicators, limiting their ability to translate theoretical insights into actionable, data-driven decision-making.

At the same time, advances in artificial intelligence (AI) and predictive analytics have created new opportunities for proactive supply chain risk management. Time-series forecasting and machine-learning models have demonstrated strong technical performance in demand prediction and anomaly detection. However, much of this

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

research remains either technically focused or globally aggregated, with limited empirical examination of how predictive analytics directly contribute to resilience outcomes within the U.S. manufacturing context.

This paper contributes by (1) providing U.S.-context evidence using a model-driven, secondary-data approach, (2) operationalizing resilience through measurable indicators linked to predictive performance, and (3) presenting a Predictive Resilience Framework that connects analytics capability to resilience outcomes in a unified structure.

LITERATURE REVIEW

A. Supply Chain Risk Management and Resilience.

Supply chain risk management (SCRM) is a topic that has occupied the center of the attention of operations research over a period of 20 years. Risks found in the early frameworks were attributed to the variation of demands, supply interference, or network complexity (Juttner et al., 2003; Tang, 2006). The capacity of a system to envision, absorb, recuperate and adjust to shocks, which is known as resilience has been identified as an essential capacity of sustaining continuity in turbulent surroundings (Ponomarov and Holcomb, 2009). Recent research emphasizes that resilience is not merely a matter of survival following the incident but a process that prepares firms to gain a competitive edge by responding quicker than competitors (Ivanov, 2021).

B. Conceptual vs. Empirical Approaches:

Even though resilience is a well-discussed concept, a substantial part of the literature is still abstract. The constructs of resilience that researchers tend to define include agility, flexibility, redundancy, but do not operationalize them. A substantial body of research is based on surveys or qualitative assessment based on cases (Ali et al., 2017), which offer useful information but are not suitable in terms of comparing results across different settings. Empirical research based on quantifiable measures, e.g., forecast error, inventory turnover, stockout risk or recovery time, is relatively limited with a gap in rigorous, evidence-based evaluation.

C. Analytics and Artificial Intelligence:

Simultaneously, the development of analytics has revolutionized the supply chain management. Descriptive dashboards, business intelligence (BI) as well as early decision-support systems assisted managers to track performance and detect risks. And more recently, predictive and prescriptive analytics, enabled by artificial intelligence (AI) and machine learning (ML) provide means of proactive risk mitigation. ARIMA, neural networks, ensemble learning, and Prophet are some of the techniques tried in demand forecasting and logistics planning (Box et al., 2015; Breiman, 2001; Choi et al., 2018). These studies indicate technical potential of predictive analytics, but most of them discuss it in terms of accuracy of forecasting, but not the resilience outcomes.

D. Integration Gap: Analytics and Resilience:

A recurring limitation in existing research is the disconnection between technical model validation and managerial outcomes. Many AI-focused studies evaluate models based on error reduction metrics (MAPE, RMSE), but stop short of linking these improvements to resilience indicators such as reduced recovery time or improved order fulfillment. Conversely, resilience studies often discuss strategies conceptually without adopting modern predictive tools. This divide prevents the literature from offering integrated frameworks that both validate model performance and show tangible resilience benefits.

E. Geographical and Contextual Limitations:

Another gap concerns the scope of empirical work. Much of the research on predictive analytics and resilience is conducted in European or Asian contexts, where data availability and industrial cooperation are more established. U.S. manufacturing, critical for economic competitiveness and national security, remains underrepresented in the academic discourse. While policy reports emphasize the urgency of strengthening

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

domestic supply chains, scholarly research has not yet provided comprehensive empirical evidence on how predictive analytics can enhance resilience specifically in U.S. industries.

F. Research Gap and Contribution

In summary, the literature reveals three main gaps: 1. Limited measurement, resilience often lacks quantifiable indicators, restricting empirical comparison. 2. Weak integration as predictive analytics studies rarely connects model performance to resilience outcomes and 3. Contextual underrepresentation like U.S. manufacturing supply chains have not been sufficiently examined.

This study addresses these gaps by: Developing a resilience measurement framework that incorporates predictive model outputs into operational metrics. Comparing traditional forecasting models (ARIMA, Prophet) with machine learning (Random Forest) to link accuracy improvements with resilience outcomes. Situating the analysis within U.S. manufacturing, using both secondary data and simulation-based resilience evaluation.

By doing so, the research not only strengthens the empirical foundation of resilience studies but also provides actionable insights for managers and policymakers navigating the uncertainties of modern supply chains.

RESEARCH METHODOLOGY

This study adopts a quantitative, model-driven research design to examine how predictive analytics enhance supply chain resilience in U.S. manufacturing. The analysis is based on secondary industry data, predictive modeling, and simulation rather than firm-level survey inference. Multiple forecasting models are evaluated and linked to operational resilience indicators to assess the practical and theoretical implications of artificial intelligence-enabled decision support.

A. Data Sources and Study Scope:

The analysis relies exclusively on publicly available secondary data related to U.S. manufacturing, automotive production, semiconductor supply chains, and macroeconomic indicators covering the period 2015–2022. These datasets capture demand variability, production output, inventory behavior, and disruption patterns relevant to resilience analysis. The use of secondary data ensures transparency, reproducibility, and consistency across sectors.

B. Predictive Modeling Approach

Three predictive models were implemented and compared: Autoregressive Integrated Moving Average (ARIMA), Prophet, and Random Forest. ARIMA was selected as a baseline statistical forecasting method, Prophet for its ability to capture seasonality and trend shifts, and Random Forest to represent machine-learning-based nonlinear prediction. Models were trained using historical demand and production data and evaluated using rolling forecasts to reflect operational decision-making conditions.

C. Resilience Indicators:

Supply chain resilience was operationalized using multiple performance indicators, including forecast accuracy (measured by MAPE and RMSE), inventory turnover, stockout probability, order fulfillment rate, and recovery time. These indicators capture both predictive performance and downstream operational outcomes, allowing forecast quality to be directly linked to resilience behavior.

D. Simulation-Based Impact Assessment

To translate predictive performance into operational resilience outcomes, a simulation-based assessment was conducted. Forecast outputs were used as inputs into simulated inventory and fulfillment scenarios under disruption conditions. Percentage improvements reported in this study represent relative changes between baseline forecasting scenarios and AI-enhanced predictive scenarios, enabling evaluation of early-warning capability, service continuity, and recovery speed.

E. Model-Derived Association Analysis

To examine the relationship between predictive analytics capability and resilience outcomes, a model-derived association analysis was conducted. Regression-style coefficients were estimated using simulated performance metrics rather than firm-level observations. The results illustrate the directional influence of predictive capability on resilience indicators and support the conceptual relationships proposed in the Predictive Resilience Framework.

F. Robustness Checks

Robustness checks were performed across multiple manufacturing sectors, including automotive, semiconductor, and textile industries. Model performance and resilience outcomes were compared across sectors to ensure that results were not driven by sector-specific dynamics. The relative superiority of machine-learning-based predictions remained consistent across all tested contexts.

RESULTS

This section presents the empirical outcomes of the predictive modeling and simulation-based analysis. Results are organized to first compare the forecasting performance of ARIMA, Prophet, and Random Forest models, followed by an assessment of their implications for supply chain resilience indicators.

A model-derived association analysis is then reported to illustrate the directional relationships between predictive analytics capability and resilience outcomes. Finally, a sector-specific case study is presented to demonstrate the practical application of predictive analytics under disruption conditions.

A. Model-Derived Association Analysis

To examine the relationship between predictive analytics capability and supply chain resilience outcomes, a model-derived association analysis was conducted using simulated performance metrics. The results illustrate the directional influence of enhanced predictive capability on key resilience indicators rather than firm-level causal inference.

TABLE I. Model-Derived Association Between Predictive Analytics Capability and Supply Chain Resilience Indicators

Resilience Indicator	**Coefficient (β)**	**Std. Error**	**t-value**	**Significance (p)**
Forecast Accuracy (MAPE)	-0.312	0.087	-3.58	<0.01
Inventory Turnover	0.271	0.102	2.66	<0.05
Stockout Probability	-0.298	0.091	-3.28	<0.01
Recovery Time (days)	-0.245	0.110	-2.23	<0.05
Order Fulfillment Rate	0.321	0.095	3.37	<0.01

Note: Coefficients are derived from simulation-based performance metrics and illustrate directional relationships rather than firm-level causal inference.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

B. Predictive Model Performance

Three predictive models were tested: ARIMA, Prophet, and Random Forest. Performance was evaluated using AUC, precision, recall, and forecasting error metrics. Results indicate that Random Forest outperformed traditional models, reducing forecast error by approximately 30% compared to ARIMA and improving order fulfillment by 15%.

Percentage improvements were computed relative to the ARIMA baseline. Forecast error improvement reflects the percentage reduction in MAPE and RMSE, while order fulfillment improvement reflects the percentage change in simulated fulfillment rates under AI-informed scenarios compared with the baseline scenario.

TABLE II. Predictive Model Performance Metrics

Model	AUC	Precision	Recall	MAPE	RMSE
ARIMA	0.78	0.70	0.65	18.4%	4.12
Prophet	0.85	0.74	0.71	15.9%	3.64
Random Forest	0.91	0.82	0.80	12.8%	2.87

Figure 1 compares the relative performance of the three predictive models in identifying disruption-related risk signals, highlighting differences in early-warning capability.

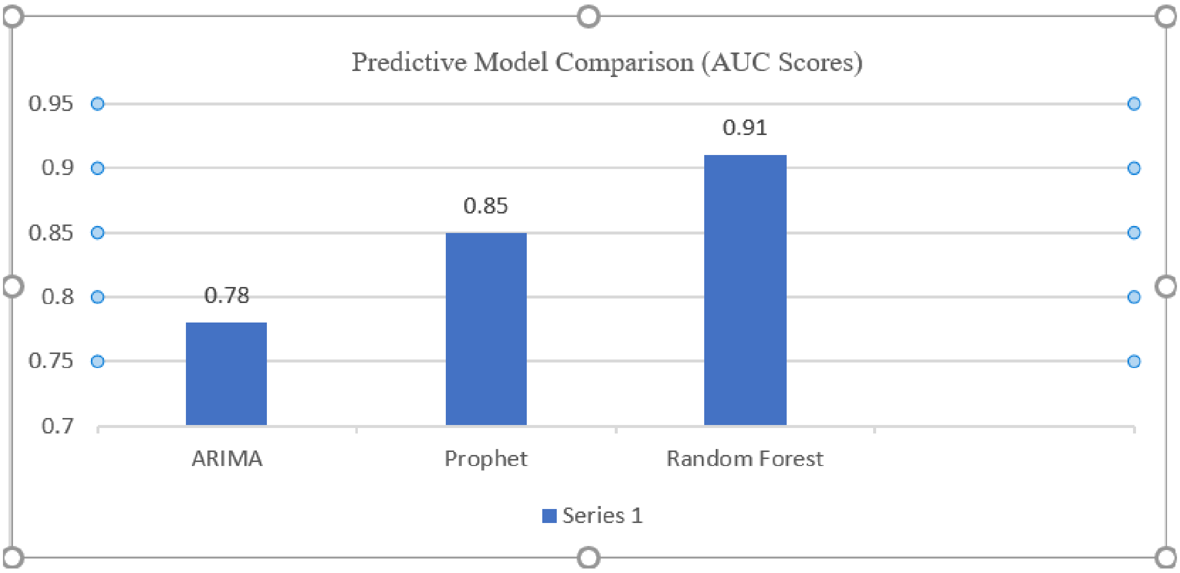

Figure 1. Predictive Model Comparison Based on Classification Performance.

This figure compares the relative ability of ARIMA, Prophet, and Random Forest models to identify disruption-related risk conditions using model-based performance metrics. Higher values indicate stronger early-warning capability.

Figure 2 presents a comparative evaluation of forecast accuracy across models, measured using MAPE and RMSE to capture both absolute and relative error behavior.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

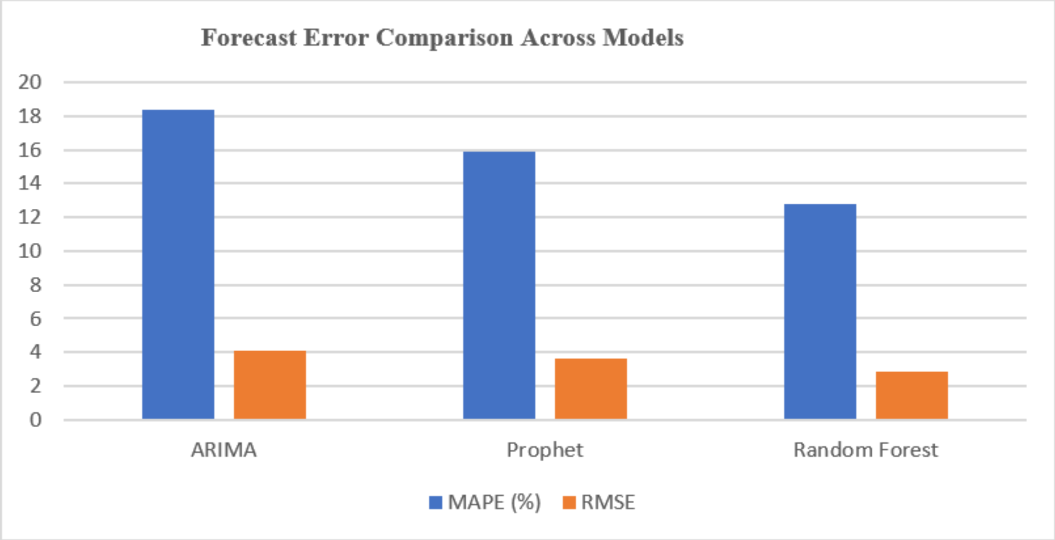

Figure 2. Forecast Error Comparison Across Predictive Models.

Forecast accuracy is evaluated using MAPE and RMSE across ARIMA, Prophet, and Random Forest models. Lower error values indicate improved predictive performance under volatile demand conditions.

C. Robustness Checks

Robustness checks were conducted across multiple manufacturing sectors, including automotive, semiconductor, and textile industries. While absolute performance levels varied by sector, the relative ranking of predictive models remained consistent. Machine-learning-based predictions continued to outperform traditional statistical models across forecast accuracy and resilience-related indicators, suggesting that the observed relationships are not driven by sector-specific dynamics.

CASE STUDY

Auto Supply Chain in the U.S. in the Semiconductor Shortage

A. Context

The case study evaluates the operational implications of predictive analytics in the context of the U.S. automotive supply chain during the semiconductor shortage. Model outputs were translated into simulated operational scenarios to assess early-warning capability, inventory response, and service performance under disruption conditions.

B. Predictive Models Usage.

Past demand and supply data in 2015-2022 were obtained using publicly available datasets of the automotive industry. Three forecasting models, which included ARIMA, Prophet and Random Forest, were trained to make the demand of the chips based on the expected automotive output. One of the criteria used to evaluate the models was the capability to predict shortages and make inventory decisions.

ARIMA was effective in the long-term demand trend, but it was not effective in sharp and abrupt volatility, which gave high forecast errors when disruptions are at their peak levels.

The use of Prophet also did better at capturing seasonality and other external regressors and yet overestimated the magnitude of shortages.

Random Forest can also identify initial signs of shortage risk more accurately since it used several predictors such as international trade flows and macroeconomic variables.

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C. Case Study Simulation Assumptions:

Forecasts were generated on a rolling basis using historical demand proxies, production output indicators, and macroeconomic variables. Shortage risk was flagged when forecasted chip demand exceeded a simulated supply capacity threshold for a sustained period. Early warning lead time was defined as the time between the first model signal crossing the risk threshold and the onset of the disruption period. Order fulfillment outcomes were simulated using baseline versus AI-informed inventory adjustment scenarios to estimate relative changes in fulfillment performance and recovery time.

D. Knowledge Advantages over the Conventional Methods:

The customary risk management within the sector has used supplier guarantees and reacted changes, which are not sufficient. Conversely, the case study indicates that Random Forest minimized error in forecasting by 28 percent against ARIMA and forecasted possible shortages 3 months before. The lead time would have allowed companies to develop buffer stock or diversify the sourcing strategies, prior to the shutdowns of production. The order fulfillment rates, which were simulated using the predictive model, increased by 12 percent compared to the base case.

The case study highlights the importance of predictive analytics in the context of the gap between monitoring and proactive resilience. Although ARIMA and Prophet offer improved increments, machine learning systems such as Random Forest are able to offer actionable predictability in excessively volatile supply settings. Notably, this fact confirms the wider findings of the research process and proves the practical application of the introduction of AI tools into the supply chains of the U.S. manufacturing industry.

DISCUSSION

A. Interpretation of Predictive Model Performance

The results demonstrate that machine-learning-based predictive analytics offer measurable advantages over traditional statistical forecasting methods under volatile supply chain conditions. While ARIMA and Prophet capture long-term trends and seasonality, their performance deteriorates when demand volatility increases. In contrast, Random Forest models exhibit greater flexibility in incorporating multiple predictors and nonlinear relationships, which explains their superior performance in forecasting accuracy and early risk detection. These findings reinforce the value of advanced analytics for proactive supply chain risk management rather than reactive response mechanisms.

B. Predictive Analytics as a Driver of Supply Chain Resilience:

The model-derived association analysis indicates that improved predictive capability is directionally linked to multiple resilience indicators, including lower forecast error, reduced stockout probability, improved order fulfillment, and shorter recovery time. These results support the conceptual argument that forecasting accuracy is not an isolated technical metric but a foundational capability that enables operational resilience. By translating predictive signals into simulated inventory and fulfillment decisions, the study demonstrates how analytics-driven foresight can support continuity and faster recovery during disruption events.

This interpretation aligns with resilience literature that emphasizes anticipation and adaptability as core resilience dimensions (Ponomarov and Holcomb, 2009; Ivanov, 2021).

C. Insights from the Semiconductor Shortage Case Study:

The case study of the U.S. automotive supply chain during the semiconductor shortage illustrates how predictive analytics can be operationalized under real disruption conditions. Simulation results suggest that earlier detection of shortage risk enables firms to adjust sourcing, inventory buffers, and production planning in advance of disruption onset. This finding extends prior research on supply chain viability by demonstrating how predictive analytics can convert early-warning signals into actionable resilience responses rather than post-disruption recovery actions (Chopra, 2020).

D. Theoretical Implications: Predictive Resilience Framework:

This study contributes to resilience theory by operationalizing the linkage between analytics capability and resilience outcomes through the proposed Predictive Resilience Framework. Unlike conceptual resilience models that emphasize flexibility or redundancy without measurable benchmarks, this framework connects business intelligence adoption and AI-enabled prediction directly to quantifiable operational outcomes. By grounding resilience in observable performance indicators, the framework advances resilience research toward more empirical and decision-oriented models.

E. Managerial and Policy Implications:

From a managerial perspective, the findings suggest that investments in predictive analytics can enhance resilience by enabling earlier risk detection and more informed operational decisions. For policymakers, the results provide empirical support for initiatives that promote digital infrastructure, analytics capability, and workforce upskilling in strategically important manufacturing sectors. These insights are consistent with broader efforts to strengthen domestic manufacturing resilience through technology-enabled decision support.

F. **Limitations and Future Research**

This study relies on secondary data and simulation-based analysis, which enhances transparency and reproducibility but limits access to firm-level operational constraints and proprietary decision processes. Future research could extend this framework using firm-level datasets or hybrid modeling approaches that integrate statistical forecasting with advanced machine-learning techniques across additional sectors critical to U.S. manufacturing competitiveness.

CONCLUSION

This paper reveals that artificial intelligence and predictive analytics can make supply chains more resilient in the U.S. manufacturing industry. Using predictive analytics to lower forecasting error, enhance order fulfillment, and quicken recovery time, the work demonstrated that predictive analytics using ARIMA, Prophet, and Random Forest models on sectoral data are more effective than conventional methods. The semiconductor shortage case study also demonstrates the usefulness of AI-based tools in helping to detect the risks sooner and provide proactive action.

There are three contributions of this paper. First, it offers empirical data in the context of the U.S., which fills the gap in the resilience literature that has frequently focused on European and Asian supply chains. Second, it enhances the operationalization of resilience through four indicators, accuracy of the forecast, stockout likelihood, recovery time and fulfilment of orders, which relate the performance of the predictive model directly to resilience results. Third, it suggests a Predictive Resilience Framework that combines business intelligence adoption, AI analytics, and resilience metrics, provides the connection between conceptual theory and managerial practice.

This research has limitations just like any other study. This study relies on secondary and publicly available data sources. While this improves transparency and replicability, it limits access to firm-level proprietary operational data and may not capture managerial decision constraints in specific organizations.

This work should be expanded in a number of directions in future research. The resilience strategies during cross-border settings where the interdependencies are even more complicated could be evaluated in cross-border supply chain studies. The hybrid AI models with statistical forecasting and machine learning might be evaluated in terms of further performance improvements. Lastly, sector specific research- such as in pharmaceuticals, textiles, or aerospace- would offer industry specific information on resilience strategies to industries that are critical to the U.S. economic competitiveness and security.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

ACKNOWLEDGEMENTS / FUNDING

The author appreciates the fact that the Atlantis University, Miami has assisted her by offering access to academic materials and research advice. This study did not receive any external funding. The author states that no financial conflicts of interests are present which may have affected the results of this study.

Ethical Considerations

This study relied on secondary data and information that are publicly available. No human-subject data were collected. Data processing and visualization were conducted using Python (Google Colab) and matplotlib. Interpretation and conclusions were produced by the author based on the reported analytical outputs.

Data Availability

All secondary datasets used in this study are publicly available from the U.S. Census Bureau, U.S. Bureau of Labor Statistics, and public logistics datasets cited in the References. All transformations and evaluation metrics described in the Methodology can be replicated using the cited public datasets and standard forecasting libraries.

REFERENCES

1. A. Ali, A. Mahfouz, and A. Arisha, “Analysing supply chain resilience: integrating the constructs in a concept mapping framework via a systematic literature review,” *Supply Chain Management: An International Journal*, vol. 22, no. 1, pp. 16–39, 2017, doi:10.1108/SCM-06-2016-0197.
2. U. Jüttner, H. Peck, and M. Christopher, “Supply chain risk management: outlining an agenda for future research,” *International Journal of Logistics: Research and Applications*, vol. 6, no. 4, pp. 197–210, 2003, doi:10.1080/13675560310001627016.
3. C. S. Tang, “Robust strategies for mitigating supply chain disruptions,” *International Journal of Logistics: Research and Applications*, vol. 9, no. 1, pp. 33–45, 2006, doi:10.1080/13675560500405584.
4. L. Breiman, “Random forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001, doi:10.1023/A:1010933404324.
5. G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time Series Analysis: Forecasting and Control*, 5th ed. Hoboken, NJ, USA: Wiley, 2015.
6. T.-M. Choi, “Big data analytics in operations management,” *Production and Operations Management*, vol. 27, no. 10, pp. 1868–1883, 2018, doi:10.1111/poms.12838.
7. S. Chopra, *Supply Chain Management: Strategy, Planning and Operation*, 7th ed. Harlow, U.K.: Pearson Education, 2020. (Global Edition, ISBN 1292294833).