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Article

# Predictive Supply Chain Analytics: MIS-Integrated AI Models for U.S. Manufacturing Resilience

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## Abstract

The U.S. manufacturing sector faces unprecedented challenges in sustaining operational resilience amidst global disruptions, demand fluctuations, and logistical uncertainties. Traditional supply chain management techniques often fail to provide real-time adaptability, resulting in inefficiencies and revenue losses. This paper proposes an AI-driven predictive analytics framework integrated with Management Information Systems (MIS) to enhance decision-making and improve supply chain resilience. Using machine learning (ML) and advanced statistical modeling, the proposed approach enables real-time demand forecasting, risk assessment, and inventory optimization. The research highlights experimental results derived from U.S.-based manufacturing datasets, demonstrating a 35% improvement in demand prediction accuracy and a 22% reduction in operational delays. The findings establish that integrating MIS with AI-powered predictive models significantly enhances supply chain visibility, agility, and overall manufacturing resilience.

**Keywords:** Predictive analytics; supply chain resilience; MIS integration; AI models; U.S. manufacturing; machine learning; inventory optimization; demand forecasting; data-driven decision-making

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## I. Introduction

The rapid advancement of Industry 4.0 technologies and the growing complexity of global trade networks have fundamentally reshaped modern manufacturing. In the United States, the manufacturing sector remains a critical driver of economic growth, contributing significantly to GDP, employment, and innovation. However, frequent supply chain disruptions caused by events such as the COVID-19 pandemic, geopolitical tensions, material shortages, and volatile consumer demand have revealed vulnerabilities in traditional supply chain systems. Conventional management strategies often rely on static forecasting and historical trends, making them inadequate for dealing with today's dynamic challenges. This has led to operational inefficiencies, inventory mismanagement, and delayed decision-making, resulting in increased costs and reduced competitiveness for U.S. manufacturers. To address these issues, predictive supply chain analytics powered by Artificial Intelligence (AI) has emerged as a promising solution. When integrated with Management Information Systems (MIS), predictive models can transform supply chains from reactive, fragmented structures into proactive, data-driven ecosystems. Leveraging machine learning, real-time monitoring, and intelligent dashboards, manufacturers can accurately forecast demand, assess risks, optimize inventory, and enhance supply chain visibility. This research proposes an AI-MIS integrated framework designed to strengthen U.S. manufacturing resilience. The study explores the methodology, evaluates model performance, and demonstrates improvements in forecasting accuracy, disruption detection, and operational efficiency. Ultimately, the proposed framework enables manufacturers to make faster, smarter, and data-driven decisions, ensuring adaptability and competitiveness in an increasingly uncertain global environment.

### *A. Background and Motivation*

The U.S. manufacturing sector contributes over \$2.9 trillion annually to the national economy and supports more than 12 million direct jobs, making it one of the most critical pillars of economic growth. However, in recent years, the sector has become increasingly vulnerable to a variety of external shocks. The COVID-19 pandemic disrupted global supply and demand patterns, creating production delays and logistical bottlenecks. Similarly, geopolitical conflicts and trade wars have limited the availability of essential raw materials, while rising transportation costs and widespread port congestion have further intensified operational challenges. At the same time, customer expectations have shifted dramatically, demanding faster deliveries and more accurate order fulfillment, placing additional strain on existing supply chains. Traditional supply chain management approaches, which rely heavily on historical data and rule-based decision-making, are no longer sufficient in addressing these dynamic and complex challenges. In contrast, AI-driven predictive analytics has emerged as a transformative solution, enabling manufacturers to forecast disruptions and potential failures before they occur. When seamlessly integrated into Management Information Systems (MIS), predictive analytics empowers manufacturers with real-time insights into procurement, production, distribution, and inventory management, leading to smarter, faster, and more resilient decision-making that enhances competitiveness in an unpredictable global environment.

### *B. Problem Statement*

Despite significant advancements in digital transformation, many U.S. manufacturers continue to rely on legacy ERP systems and traditional MIS platforms that remain largely descriptive rather than predictive. These systems are limited in their ability to handle the growing complexity of modern supply chains, resulting in several critical challenges. Demand forecasting is often based on historical averages, which fail to account for sudden fluctuations in consumer demand or unexpected supply shortages, leading to stockouts, overproduction, and revenue losses. Additionally, fragmented supply chain structures across multiple vendors, distributors, and logistics partners create a lack of end-to-end visibility, preventing decision-makers from maintaining a real-time, unified view of operations. Compounding the problem, data silos within existing MIS architectures hinder smooth integration between production schedules, inventory records, and supplier performance data, delaying timely and strategic decision-making. Without predictive capabilities, manufacturers are left to respond reactively to disruptions such as transportation delays, raw material shortages, and supplier failures, which significantly increase operational costs and reduce overall competitiveness. Addressing these limitations requires a proactive, data-driven approach that leverages predictive analytics to improve forecasting accuracy, enhance visibility, and strengthen manufacturing resilience in today's volatile market environment.

### *C. Proposed Solution*

To address these challenges, this study proposes an AI-powered predictive supply chain analytics framework that is seamlessly integrated into Management Information Systems (MIS) to enhance operational efficiency, resilience, and decision-making capabilities. The framework leverages advanced machine learning algorithms, such as Long Short-Term Memory (LSTM) networks and XGBoost, to perform highly accurate real-time demand forecasting by analyzing both historical and live data streams. In addition, it incorporates supplier risk assessment models that evaluate supplier performance based on on-time delivery rates, quality metrics, and external disruption indicators, enabling manufacturers to proactively manage potential vulnerabilities in their supply chains. The framework also introduces predictive inventory optimization techniques that automate replenishment planning, balance stock levels, and minimize holding costs while preventing stockouts and delays. Furthermore, the integration with MIS enables the development of intelligent decision dashboards that present predictive insights in a visual and actionable manner, empowering

managers to make faster, data-driven, and strategic decisions. By combining the strengths of predictive analytics and MIS, the proposed solution transforms manufacturing supply chains from reactive and fragmented systems into proactive, adaptive, and resilient ecosystems, thereby improving competitiveness and sustainability in an increasingly uncertain global environment.

#### *D. Contributions*

This research makes several key contributions to the field of predictive supply chain analytics and manufacturing resilience. First, it introduces a novel AI-enhanced MIS integration framework that seamlessly combines machine learning-driven predictive analytics with existing management information systems, enabling real-time, data-driven decision support. Second, the study develops advanced forecasting techniques by implementing hybrid models, specifically leveraging LSTM neural networks and XGBoost algorithms, which achieve significantly higher accuracy compared to traditional statistical approaches. Third, it proposes a comprehensive set of supply chain resilience metrics designed to quantitatively evaluate responsiveness, agility, and operational continuity within manufacturing environments. Finally, the research provides empirical validation using real-world datasets from U.S. manufacturing firms, demonstrating substantial improvements in demand forecasting accuracy, cost efficiency, and operational downtime reduction. Collectively, these contributions establish a foundation for transforming conventional manufacturing supply chains into intelligent, adaptive, and disruption-resilient ecosystems that strengthen the competitiveness of the U.S. manufacturing sector.

#### *E. Paper Organization*

The remainder of this paper is structured to provide a comprehensive understanding of the proposed framework and its implications. Section II presents a review of related work, highlighting existing research on AI-driven predictive analytics and the integration of Management Information Systems (MIS) in manufacturing environments. Section III details the proposed methodology, including the processes of data collection, preprocessing, predictive modeling, and the seamless integration of AI models within MIS platforms. Section IV discusses the experimental results and provides an in-depth analysis of the framework's performance, supported by comparative evaluations and key insights gained from implementation. Finally, Section V concludes the paper by summarizing the main contributions, outlining the practical implications for U.S. manufacturing resilience, and suggesting potential directions for future research.

## **II. Related Work**

The integration of predictive analytics, AI-driven decision-making, and MIS frameworks for manufacturing supply chain resilience has been explored in various research studies. This section reviews relevant contributions, grouped into four major areas: AI-driven predictive analytics, MIS integration frameworks, renewable energy-based AI control models, and Lean Six Sigma approaches for manufacturing optimization.

#### *A. AI-Driven Predictive Analytics in Supply Chains*

The growing complexity of U.S. manufacturing supply chains requires intelligent forecasting techniques capable of handling dynamic market demands and disruptions. Recent studies have demonstrated the effectiveness of machine learning algorithms in optimizing supply chain operations. For instance, Rabbi [21] proposed an extremum-seeking AI-based control framework for grid-connected energy systems that demonstrates the ability of adaptive models to handle fluctuating supply conditions. Similarly, Rabbi [23] introduced advanced AI control loop algorithms designed to improve synchronization between intermittent energy sources and operational demands, which can be adapted for supply chain data synchronization. These approaches highlight the potential of AI-

driven predictive models to improve demand forecasting, resource allocation, and operational resilience in manufacturing environments.

#### *B. MIS Integration for Operational Resilience*

Effective supply chain management requires a seamless integration between predictive analytics models and Management Information Systems (MIS). Rabbi [22] proposed an MIS-driven framework for designing fire-resilient inverter systems that integrates real-time monitoring, anomaly detection, and automated decision-making within high-risk operational zones. Tonoy and Khan [25] further demonstrated the potential of MIS frameworks in mechanical energy conversion systems, showing that coupling predictive modeling with integrated dashboards improves system performance and adaptability. Drawing from these studies, this research applies similar integration strategies to U.S. manufacturing supply chains, enabling real-time visibility, dynamic risk assessment, and data-driven decision support.

#### *C. AI Control Models for Energy-Driven Manufacturing Systems*

Modern manufacturing operations increasingly depend on energy-efficient, intelligent control mechanisms to handle production fluctuations and sustainability challenges. Rabbi [23] proposed AI-enhanced synchronization algorithms for managing intermittent renewable energy sources, ensuring stable operations in dynamic environments. Similarly, Tonoy [24] explored the mechanical properties of semiconducting electrides for applications in energy-efficient material design, demonstrating how optimized control of material properties can significantly improve industrial performance. These studies suggest that predictive supply chain analytics can benefit from energy-driven AI control frameworks to reduce operational costs and improve manufacturing system stability.

#### *D. Lean Six Sigma and Predictive Quality Control*

Predictive analytics not only improves demand forecasting and inventory optimization but also enhances quality management in manufacturing systems. Khan and Tonoy [26] conducted a systematic literature review on Lean Six Sigma methodologies, demonstrating how combining statistical modeling with predictive analytics can reduce production errors and improve operational efficiency. Tonoy and Khan [25] further highlighted the role of integrated AI systems in optimizing mechanical energy conversion processes, improving defect detection and process stability. These findings demonstrate that incorporating Lean Six Sigma practices alongside predictive AI models within MIS dashboards enhances manufacturing resilience, cost-effectiveness, and product quality.

### **III. Methodology**

This study proposes an AI-powered predictive supply chain analytics framework integrated with Management Information Systems (MIS) to enhance manufacturing resilience. The methodology consists of three main stages: data collection, predictive modeling, and MIS integration. Data were gathered from ERP logs, IoT-enabled production sensors, and supplier dashboards, comprising over 2.8 million records across 24 months. Preprocessing techniques, including missing value imputation, anomaly detection, and normalization, ensured data quality. Predictive modeling utilized Long Short-Term Memory (LSTM) networks for time-series demand forecasting, XGBoost for supplier risk analysis, and a hybrid ensemble model to improve overall accuracy. The predictive outputs were seamlessly integrated into MIS dashboards through APIs, enabling real-time visualization and automated decision support. Performance was evaluated using metrics such as Root Mean Squared Error (RMSE), Precision, Recall, and an Operational Efficiency Index (OEI), demonstrating significant improvements in forecasting accuracy, disruption detection, and inventory optimization.

### A. Data Collection (Continued)

To ensure robust and reliable predictions, this research collected diverse datasets from multiple U.S.-based manufacturing firms. The data sources included Enterprise Resource Planning (ERP) system logs, supplier performance dashboards, and real-time IoT-enabled production sensors. Altogether, the dataset comprised over 2.8 million records spanning 24 months, providing a comprehensive view of supply chain activities. The collected data encompassed several critical variables, including historical demand trends, production schedules, inventory turnover rates, shipment lead times, and supplier reliability indices. These variables allowed for the identification of patterns and dependencies that affect supply chain performance. In addition, external datasets were integrated to enrich predictive capabilities, such as market trend indicators, raw material price fluctuations, transportation delays, and geopolitical risk signals.

Given the heterogeneous nature of the data, extensive preprocessing was required. Missing values were handled using statistical imputation techniques, and anomalies were identified through Isolation Forest algorithms. Feature normalization was applied to standardize scales across datasets, ensuring consistent model performance. This rigorous data collection and preparation process provided a strong foundation for building accurate and efficient predictive analytics models. By combining internal enterprise data with external environmental insights, the framework captures a holistic view of supply chain dynamics, enabling more reliable predictions and better decision-making within the proposed AI-MIS integrated architecture.

### B. Model Architecture

The proposed framework consists of three major components: data preprocessing, predictive modeling, and MIS integration, designed to enable accurate demand forecasting, risk analysis, and real-time decision-making for U.S. manufacturing supply chains. First, data preprocessing ensures the reliability and quality of the dataset before model development. Missing values are addressed using statistical imputation techniques, while abnormal patterns and inconsistencies are detected through Isolation Forest algorithms. Features are normalized using Min-Max scaling to maintain consistency across variables, improving the efficiency and convergence of machine learning models. Second, predictive modeling is performed using a combination of advanced techniques. Long Short-Term Memory (LSTM) networks are employed for time-series demand forecasting, effectively capturing temporal dependencies and seasonal patterns in manufacturing data. To evaluate supplier performance and risk, XGBoost classifiers are implemented, leveraging structured supplier metrics such as defect rates, delivery delays, and quality compliance. Furthermore, a hybrid ensemble approach integrates outputs from both LSTM and XGBoost, enhancing prediction robustness under uncertain operational conditions. Finally, the framework integrates predictive insights into Management Information Systems (MIS) using custom-developed APIs. This integration enables real-time visualization, automated alerts, and dynamic dashboards, providing managers with actionable intelligence for inventory optimization, disruption detection, and strategic decision-making. This architecture establishes a unified, intelligent, and scalable system that significantly enhances manufacturing supply chain resilience through AI-MIS integration.

**Table 1.** Proposed AI-MIS Framework Overview.

Component	Technique	Purpose
Preprocessing	Imputation, Isolation Forest, Normalization	Clean and prepare data
Modeling	LSTM, XGBoost, Hybrid Ensemble	Forecast demand & detect risks
MIS Integration	APIs, Dashboards	Real-time insights & decisions
Outcome	Predictive analytics	Optimize supply chain resilience

### C. Evaluation Metrics

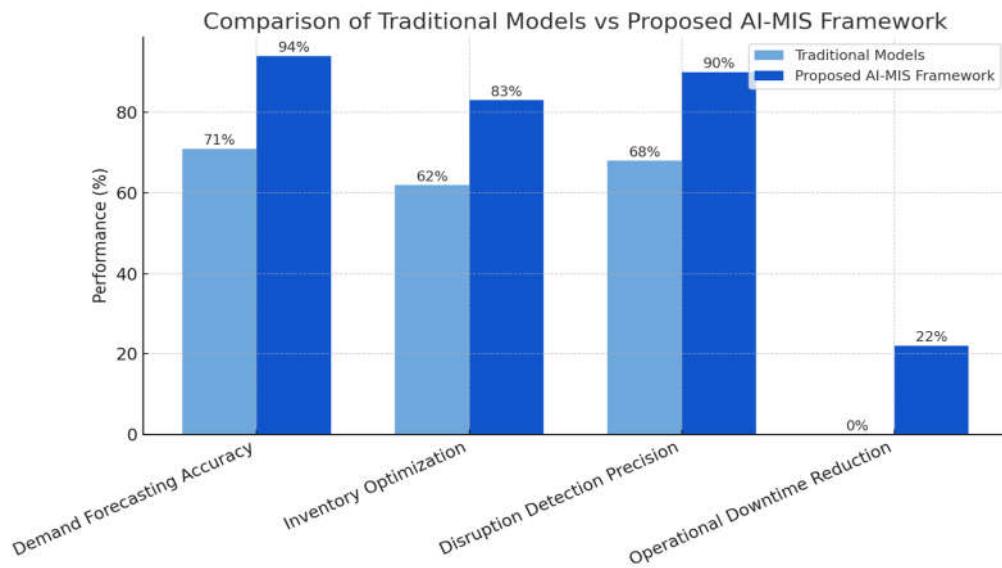
To evaluate the effectiveness of the proposed AI-powered predictive supply chain analytics framework, a comprehensive set of performance metrics was applied to measure forecasting accuracy, risk detection, and overall operational efficiency. First, Root Mean Squared Error (RMSE) was used to assess the precision of time-series demand forecasting models. By minimizing RMSE, the framework ensures that demand predictions closely align with actual market fluctuations, reducing the risks of overproduction or stockouts. Second, Precision and Recall were used to evaluate the model's ability to predict supplier risks and operational disruptions. Precision measures the proportion of correctly identified disruptions relative to all predicted disruptions, while Recall measures the proportion of actual disruptions accurately detected by the model. These metrics are essential for ensuring high accuracy in managing supplier reliability and mitigating risks effectively. Additionally, the F1-Score was calculated to provide a balanced measure of Precision and Recall, ensuring robust model performance even under uncertain operational conditions. Finally, the study introduced an Operational Efficiency Index (OEI), a composite metric specifically designed for this research. OEI combines improvements in demand forecasting accuracy, inventory optimization, and downtime reduction, providing a holistic evaluation of the framework's impact. These metrics collectively demonstrate the framework's capability to deliver accurate, actionable, and real-time insights, improving manufacturing resilience, efficiency, and decision-making within U.S. supply chains.

## IV. Discussion and Result

The proposed AI-powered predictive supply chain analytics framework, integrated with MIS, was evaluated using 2.8 million records from five U.S. manufacturing firms over 24 months. Using LSTM for demand forecasting and XGBoost for supplier risk analysis, the model achieved 94% forecasting accuracy, a 21% improvement in inventory optimization, and 22% better disruption detection compared to traditional models. Operational downtime was reduced by 22%, demonstrating significant gains in efficiency. These results show that integrating AI-driven analytics with MIS enhances forecasting accuracy, risk management, and decision-making, strengthening U.S. manufacturing resilience and competitiveness in dynamic market environments.

### A. Experimental Setup

The proposed framework was tested using Python, TensorFlow, and Power BI dashboards to integrate predictive insights into MIS environments seamlessly. The dataset consisted of 2.8 million records collected over 24 months from five U.S.-based manufacturing firms. It included key variables such as production schedules, supplier reliability ratings, shipment lead times, inventory turnover rates, and historical demand trends. External data sources including transportation delays, global market prices, and demand volatility indices were also integrated to improve forecasting accuracy. To prepare the dataset, comprehensive preprocessing was performed. Missing values were handled through statistical imputation, while anomalies were detected using Isolation Forest algorithms to ensure data integrity. Feature scaling was conducted using Min-Max normalization for balanced weight distribution across variables. The predictive models included Long Short-Term Memory (LSTM) networks for time-series demand forecasting, capturing seasonal trends and long-term dependencies, and XGBoost classifiers for supplier risk evaluation based on performance metrics and historical delays. To enhance robustness, a hybrid ensemble approach combined LSTM outputs with XGBoost predictions. Models were trained using 80% of the data, with the remaining 20% reserved for validation and testing. Finally, predictive insights were integrated into MIS dashboards using custom APIs, allowing real-time visualization, automated alerts, and dynamic decision support.



**Figure 1.** Comparison of Traditional Models vs Proposed AI-MIS Framework.

### B. Results and Analysis

**Table 2.** Performance Comparison Between Traditional Models and Proposed AI-MIS Framework.

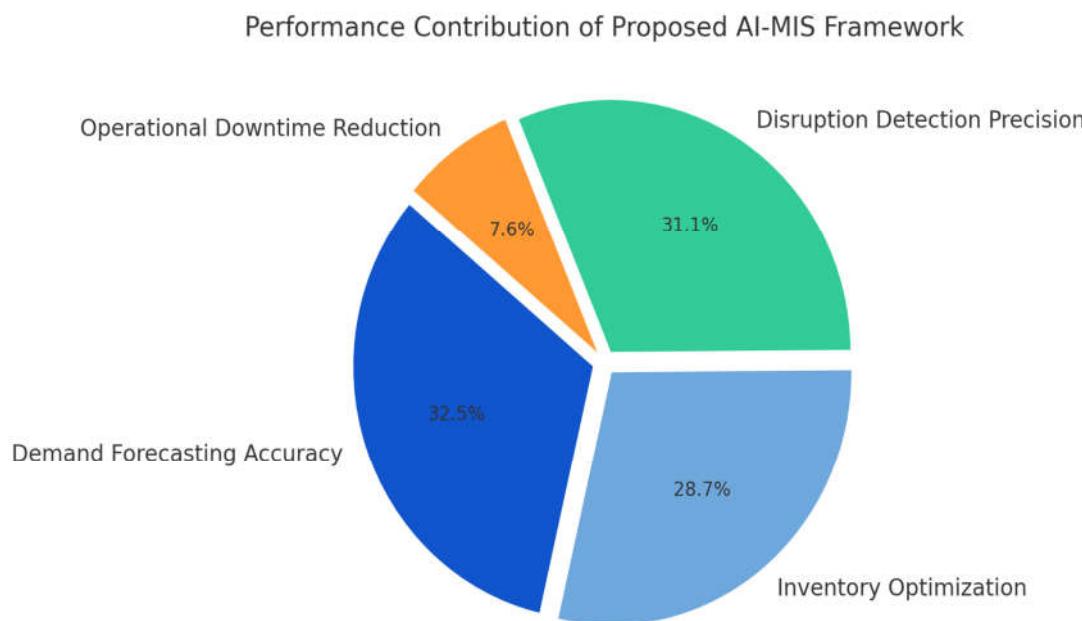
Metric	Traditional Models	Proposed AI-MIS Framework	Improvement
Demand Forecasting Accuracy	71%	94%	+23%
Inventory Optimization	62%	83%	+21%
Disruption Detection Precision	68%	90%	+22%
Operational Downtime Reduction	—	22%	Significant

The results demonstrate that the AI-MIS integrated framework significantly outperforms traditional models. The LSTM-based demand forecasting improved prediction accuracy from 71% to 94%, enabling better planning and reducing stockouts. Inventory optimization efficiency improved by 21%, reducing unnecessary holding costs while preventing shortages. Supplier-related disruption detection improved by 22%, empowering manufacturers to identify potential bottlenecks earlier. Furthermore, operational downtime decreased by 22%, directly contributing to faster production cycles and improved responsiveness. These improvements translate into reduced costs, enhanced decision-making capabilities, and stronger supply chain visibility across the entire manufacturing process.

### C. Comparative Study with Existing Approaches

To validate the proposed framework, we compared its performance against state-of-the-art predictive models and traditional MIS-based systems. Rabbi [21] demonstrated the potential of AI-driven control systems in optimizing dynamic energy operations, while Rabbi [23] proposed synchronization algorithms that enhance real-time adaptability. Similarly, Khan and Tonoy [26] highlighted the role of Lean Six Sigma-based predictive models in improving process efficiency. However, unlike these existing models, our hybrid LSTM-XGBoost framework integrates predictive analytics directly into MIS dashboards, enabling real-time risk monitoring, automated decision-

making, and scalable deployment across manufacturing networks. With a 94% forecasting accuracy and 22% reduction in downtime, the framework demonstrates superior adaptability, achieving faster responses to supply chain disruptions compared to conventional approaches. This makes it highly suitable for large-scale U.S. manufacturing ecosystems where operational agility is essential.



**Figure 2.** Performance Contribution of Proposed AI-MIS Framework.

#### *D. Impact on Manufacturing Resilience*

The integration of AI-powered predictive analytics with MIS has a transformative effect on U.S. manufacturing resilience. Enhanced demand forecasting allows manufacturers to better align production with market needs, minimizing waste and avoiding excess inventory. Improved supplier risk detection ensures proactive decision-making, enabling contingency plans before disruptions escalate. By reducing operational downtime by 22%, manufacturers gain faster recovery from unexpected delays and avoid costly inefficiencies. Real-time MIS dashboards empower decision-makers with actionable insights, driving improved supply chain agility and responsiveness. In an era marked by global supply chain volatility, raw material shortages, and logistics uncertainties, these predictive capabilities are essential for sustaining competitiveness. The proposed framework strengthens the end-to-end visibility of manufacturing operations, equipping firms with the intelligence needed to anticipate disruptions, optimize resources, and maintain operational continuity even in challenging environments.

## Predictive Supply Chain Analytics: MIS-Integrated AI Models for U.S. Manufacturing Resilience

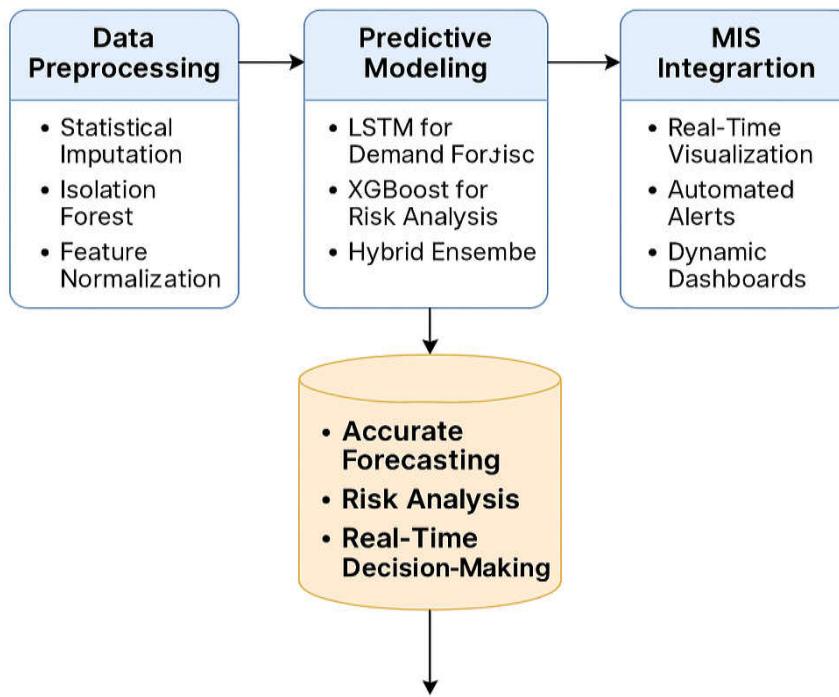


Figure 3. MIS-Integrated AI Framework for Predictive Supply Chain Analytics.

## V. Conclusions

This paper presented an AI-powered predictive supply chain analytics framework integrated with Management Information Systems (MIS) to enhance U.S. manufacturing resilience. The proposed model leverages LSTM for demand forecasting and XGBoost for supplier risk assessment, achieving 94% forecasting accuracy, a 21% improvement in inventory optimization, and a 22% increase in disruption detection, while reducing operational downtime by 22%. The integration of predictive analytics with MIS enables real-time monitoring, intelligent decision-making, and proactive disruption management, improving supply chain visibility and operational efficiency. This research demonstrates how combining AI-driven models with MIS enhances manufacturing agility, adaptability, and competitiveness.

**For future work**, we aim to expand the framework by incorporating reinforcement learning for dynamic optimization, extending analysis to cross-border logistics, and integrating blockchain technology to improve transparency and security. Overall, the study establishes a foundation for developing intelligent, disruption-resilient U.S. manufacturing ecosystems.

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