Supply Chain Resilience System using AI and ML

Birampally Srichakra Prasad Rao[1], B S V K A Chandrahaas[2], Doli Sai Vishal[3], Vallala Mahender[4]

[1]Department of Information Technology, ACE Engineering College
[2]Department of Information Technology, ACE Engineering College
[3]Department of Information Technology, ACE Engineering College
[3]Department of Information Technology, ACE Engineering College

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Abstract - This paper presents a Supply Chain Resilience System that uses Artificial Intelligence (AI) and Machine Learning (ML) to help managers make better inventory and risk decisions. The system goes beyond simple sales forecasts by taking into account real-world external factors like geopolitical instability and severe weather. It uses an XGBoost-based prediction engine to classify the inventory state into three categories: Stock-Out Risk, Excess Inventory Risk, or Low Risk. Once a risk is detected, the system immediately gives a specific, numbered action, such as exactly how many units to order. The Gemini API is used to turn the numerical results into a clear, easy-to-read executive summary. The platform also includes an Explainable AI (XAI) feature that shows which input factors contributed most to the risk score, making the system transparent and trustworthy. A role-based dashboard separates the experience for executives and analysts, so each user gets the right information for their job. All prediction records are saved to Firebase Firestore, creating a useful history for future review. The system was built using Next.js for the frontend, FastAPI for the backend, and MongoDB Atlas for data storage. Testing showed that the system delivers predictions in under one second and handles all major workflows reliably.

Key Words: *Supply Chain, Artificial Intelligence, Machine Learning, XGBoost, Risk Management, Inventory Optimization, Gemini API, Explainable AI.*

1. INTRODUCTION

Modern supply chains face constant disruptions from geopolitical tensions, extreme weather, and sudden shifts in demand. Traditional planning tools rely on historical averages and manual spreadsheet entries, which means they can only react to problems after they have already happened. This reactive approach leads to stock-outs, excess inventory, and wasted time for managers who have to figure out solutions on their own.

The Supply Chain Resilience System addresses this problem by using AI and ML to predict inventory risks before they become a crisis. At its core, the system runs an XGBoost classifier that looks at multiple risk factors at the same time, including inventory levels, lead times, demand variance, and a custom Geopolitical Risk (GPR) score. The model classifies the situation into one of three states and immediately tells the user what specific action to take.

The system is designed with two types of users in mind: analysts who run the predictions and executives who need a clear, high-level summary of the results. The Gemini API handles the translation of raw numbers into professional summaries. The XAI breakdown chart makes sure that neither user has to trust a black box, as they can always see exactly why a certain risk score was generated.

2. LITERATURE SURVEY

Several recent studies from IEEE directly shaped the design of this system.

Sahab and Oulfarsi (2024) studied supply chain risk management under disruption risks and found that modern global supply chains are becoming increasingly fragile due to complex network connections. Their work confirmed that managing disruptions remains an ongoing, unresolved challenge for businesses, even with existing software. This validated the need for a proactive AI-driven tool.

Jayasinghe et al. (2023) studied risk in green supply chain management and found that a single, generic risk mitigation strategy cannot work across different industries. This directly influenced the design of the custom Industry Type selector in our system, which adjusts the weight given to the Geopolitical Risk Score depending on the specific business context.

Abderrazak and Youssef (2022) argued that supply chain innovation itself creates new risks that must be actively monitored. Their work supports the need for Explainable AI (XAI), as managers cannot just trust a black box. They need to see the risk drivers clearly, which our bar chart visualization provides.

3. EXISTING AND PROPOSED SYSTEM

3.1 Existing System

The traditional approach to supply chain planning depends on historical data and manual spreadsheet entries. This legacy setup is reactive in nature, meaning that planners only respond to inventory problems after they have already occurred. These tools rely on simple averages, are blind to external chaos like port strikes or political instability, and use static formulas that fail when real-world volatility increases. The process is slow, people-driven, and cannot keep pace with fast-moving global logistics.

3.2 Proposed System

The proposed system introduces a predictive, AI-powered web assistant that replaces guesswork with data-driven decisions. Key improvements include: an XGBoost prediction engine that classifies inventory risk in under one second; a custom Geopolitical Risk Score that factors in global instability traditional tools ignore; automated prescriptive actions that give the exact number of units to order or reduce; a Gemini API integration that converts complex statistics into plain-language executive summaries; and a role-based dashboard that keeps the right information in front of the right person. All results are saved to a cloud database, building an audit trail for future reference.

4. SYSTEM DESIGN AND ARCHITECTURE

The system is built on a hybrid architecture split across three environments. The Client-Side Environment runs the Next.js dashboard in the user's browser. The Cloud Service Environment uses Firebase for authentication and data storage, and the Gemini API for generating summaries. The Server-Side Environment hosts the Python FastAPI backend and the trained XGBoost model.

Data flows in a strict pipeline: user input goes to the ML engine, which returns a risk classification and prescriptive action. These results are sent to the Gemini API for summarization, and everything is then saved to MongoDB Atlas. The Executive Dashboard shows high-level summaries and trends, while the Analyst Dashboard provides the detailed input form and XAI breakdown chart.

5. MODULES

5.1 Data Engineering and Preprocessing

This module cleans the raw DataCo Global Supply Chain dataset by removing irrelevant columns, handling missing values through statistical imputation, and encoding categorical text features into numerical IDs using Label Encoding. A custom Geopolitical Risk Index is mapped to different global markets with weighted scores from 1 to 10. Features that would only be known after shipment completion are excluded to prevent data leakage.

5.2 Machine Learning Model Development

XGBoost was chosen for its ability to find complex, non-linear patterns in logistics data. The data is split by time rather than randomly, so the model is trained on historical records and tested on recent ones. The model predicts both the probability of a delay and the forecasted demand. Dynamic, risk-adjusted inventory logic replaces static safety stock rules, increasing recommendations when the risk score is high. The trained model is saved in binary format for instant loading during real-time predictions.

5.3 Intelligent Backend API

The FastAPI backend serves as the central orchestrator. It receives user inputs, runs them through the ML model, calls the Gemini API for summary generation, and stores the results in MongoDB Atlas. Firebase Admin SDK middleware verifies JSON Web Tokens (JWT) so that only authorized users can access the prediction routes. Every prediction and its AI summary are stored as a historical audit record.

5.4 Frontend Dashboard and Integration

The frontend is built with Next.js 15 and styled using Tailwind CSS and HeroUI components. The Analyst dashboard provides an input form where users can enter inventory data and run a prediction. The Executive dashboard displays AI-generated summaries and historical trends. Charts built with Recharts visualize the XAI breakdown and demand versus stock levels. The interface is fully responsive and works on both desktop and mobile browsers.

6. RESULTS AND TESTING

The system was tested across unit, integration, and system levels. Unit testing confirmed that all individual components, including authentication, the ML engine, summary generation, and form validation, work correctly on their own. Integration testing verified that the frontend, backend, ML model, Firebase, and Gemini API communicate properly with each other. System testing covered the complete analyst and executive workflows, multi-company data isolation, role-based access control, and end-to-end data persistence after logout and login.

All test cases passed successfully. The core ML prediction is delivered to the screen in under one second. The Gemini API summary is generated within a few seconds and handles temporary failures gracefully using retry logic. Output screens confirm that the dashboard correctly displays delay probability, resilience score, recommended order quantity, inventory breakdown, and risk indicator charts for the analyst, and the AI summary view for the executive.

7. CONCLUSIONS

This Supply Chain Resilience System successfully shows that intelligent technology can replace slow, guesswork-based supply chain planning. The system uses Machine Learning to predict future inventory risks and customizes those predictions using real-world factors like geopolitical tension. The Gemini API then turns complex statistics into clear, actionable instructions that any manager can understand and act on immediately.

The combination of fast predictions, transparent XAI breakdowns, and role-based dashboards solves three problems at once: managers can see a problem coming, understand why the system flagged it, and know exactly what to do about it. The system sets a practical standard for how AI can be used to protect supply chain operations and keep businesses stable in an uncertain world.

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