Empirical Study and Application of Pharmaceutical Supply Chain Risk Perception based on AI Prediction and Optimization Models

Chen Yang*

University of Southampton, Southampton, United Kingdom

*yangchenac@outlook.com

Abstract

The stability and reliability of medical supply chains are closely tied to both patient safety and the quality of healthcare services. In this paper, we address the issue of predicting supply disruption risks within medical supply chains. To do this, we develop a risk prediction model based on XGBoost and several time-series forecasting approaches. The model's accuracy is further improved by incorporating dynamic factors such as inventory turnover rates and supplier ratings. We then conduct comparative experiments under four representative medical scenarios-including raw material shortages, sudden demand spikes, and logistics bottlenecks like port strikes-to assess the predictive performance of three time-series models: ARIMA, LSTM, and Transformer. The experimental findings indicate that in medical transportation scenarios, the LSTM model delivers the most accurate predictions of supply disruption risks. On the other hand, when it comes to emergency resource allocation, the Transformer model shows a clear advantage in issuing early warnings more promptly than conventional approaches, mainly because of its strength in capturing sudden and unexpected events. This study is not without limitations. For example, it does not take into account certain scenarios such as cold chain supply logistics. In addition, because of computational restrictions, the current models still face challenges in handling real-time, high-dimensional data. Looking ahead, future work could improve both accuracy and practical applicability by integrating IoT data or by refining hybrid model architectures.

Keywords

Pharmaceutical logistics, deep learning (LSTM/Transformer), supply chain resilience, time-series prediction, AI-based optimization.

1. Introduction

1.1. Background

The global pharmaceutical supply chain is currently facing unprecedented systemic challenges. The COVID-19 pandemic, escalating geopolitical conflicts, increasing extreme weather events, and volatile market demand have created a complex risk matrix, triggering frequent shortages of critical medicines, supply chain disruptions, and cost surges worldwide. This situation exposes fundamental vulnerabilities in the current system - the inherent tension between its globalized structure and strict regulatory requirements, coupled with the inability of traditional linear management models to adapt to nonlinear risks. Emerging technologies like artificial intelligence offer promising solutions through real-time risk monitoring, predictive analytics, and dynamic optimization, potentially transforming the system into a more resilient structure. However, effectively translating these technological innovations into practical solutions remains a critical challenge for both academia and industry.

1.2. Research Objectives

This research provides a systematic investigation into how AI-powered risk prediction and response mechanisms can reinforce the resilience of pharmaceutical supply chains, focusing on three critical questions.

The first question addresses whether deep learning-based prediction models are capable of detecting supply disruptions both earlier and more accurately than conventional statistical methods. Traditional approaches often face limitations due to their reliance on linear assumptions and restricted historical datasets. In this study, we examine not only the technical advantages of these advanced algorithms but also their practical applicability across various real-world scenarios within pharmaceutical operations.

Second, how can AI-enabled dynamic response strategies-such as real-time inventory optimization, adaptive allocation mechanisms, and intelligent distribution networks-contribute to significantly reducing the recovery period after supply disruptions occur? Beyond speed of response, this question also considers whether these technologies can maintain service continuity and minimize negative impacts on healthcare systems during crises.

Third, can AI models effectively lower the overall cost of emergency responses-including expenses related to redundant inventory holding, last-minute procurement, and urgent logistics-by making use of more accurate demand forecasting and resource optimization techniques? In addition, this question investigates whether cost reduction can be achieved without sacrificing supply reliability or patient safety.

Through a comprehensive and multidimensional empirical analysis, this research will not only demonstrate AI's comparative advantages in prediction accuracy, response timeliness, and cost efficiency, but will also establish a practical and theoretically grounded framework for intelligent risk management. The findings are expected to provide a solid academic foundation and actionable guidance for the ongoing digital transformation of pharmaceutical supply chains. Ultimately, the outcomes of this work will contribute to greater stability in global medicine supply and enhanced capacity to respond effectively to large-scale public health emergencies, thereby safeguarding both societal well-being and healthcare system sustainability.

2. Literature Review

The stability of pharmaceutical supply chains is critical to public health security. However, in recent years, global disruptive events such as the COVID-19 pandemic, geopolitical conflicts, and natural disasters have frequently impacted medical supply chains, leading to recurrent issues including shortages of essential medicines and logistics disruptions [1]. Under this context, enhancing the resilience of pharmaceutical supply chains and leveraging AI-powered prediction and optimization models to strengthen risk perception and response capabilities have emerged as key research priorities for both academia and industry.

2.1. Scenario and Industry Applicability

Pharmaceutical supply chains are characterized by high regulatory requirements, long lead times, and demand uncertainty, making them particularly vulnerable to external shocks. Recent studies have identified key risks including supply-side risks such as raw material shortages, production disruptions, and supplier dependency [2]; Demand-side risks, such as sudden demand surges (e.g., vaccine requirements during pandemics) and logistics risks in transportation, lead to delivery delays and insufficient warehousing capacity.

Policy and compliance risks, including variations in drug regulations across countries, pose threats to local healthcare systems [3]. To address these challenges, supply chain resilience (SCR) has emerged as a critical research focus [4]. Empirical studies demonstrate that supply chain resilience exerts significant positive effects in pharmaceutical supply chains, particularly in transportation disruption scenarios, where it effectively maintains operational performance [5].

2.2. Development of AI Predictive Models

The application of AI technology in supply chain risk prediction has grown rapidly. Machine learning (ML) and deep learning (DL)-based demand forecasting, along with time series prediction models (such as LSTM and Transformer), are now widely used for pharmaceutical demand forecasting. These approaches enable supply chain managers to better quantify resilience and optimize post-disruption system performance [6]. Deep Reinforcement Learning (DRL) frameworks can be effectively applied to optimize ordering and allocation decisions in three-tier pharmaceutical supply chains (PSCs). This approach enables distributors to function as autonomous agents (DRL agents), which play a crucial role in strategic decision-making within the DRL paradigm.

Smart Pharmaceutical Supply Chain (SmartPSC) employs digital technologies to integrate and enhance pharmaceutical manufacturing supply chains, improving efficiency, productivity, flexibility, resilience, and sustainability [7-9]. During the COVID-19 pandemic, Supply Chain 4.0 technologies - including IoT, AI-powered big data analytics, blockchain, and robotics - fundamentally transformed pharmaceutical companies' operations to ensure reliable medicine availability [10].Meanwhile, in supplier oversight, pharmaceutical companies have adopted hybrid approaches combining Z-number Data Envelopment Analysis (Z-DEA) models with Artificial Neural Networks (ANNs), achieving 83% accuracy in detecting supplier inefficiencies - a capability that reduces disruption risks by proactively identifying underperforming partners [11].

2.3. Optimization of Response Strategies

AI optimization models are also widely applied in resilient supply chain response strategies. The hospital information management of pharmaceutical supply chains, based on digital artificial intelligence + vendor-managed inventory (AI + VMI), has reduced the hospital inventory growth rate and annual average inventory error rate while improving supply chain efficiency [12]. The NSGA-II algorithm model focuses on optimizing carbon emissions, fuzzy pharmaceutical demand, travel time, and energy consumption to enhance the economic impact and service quality of PCCL [13]. Virtual tools, including artificial intelligence, blockchain, virtual reality, and augmented reality, can enhance clinician and medication accessibility while improving real-time diagnosis and treatment [14].The integration of two transformative technologies-blockchain and the Internet of Things (IoT)-enables streamlined administrative processes, optimized pharmaceutical supply chain management, remote patient monitoring, medical equipment tracking, drug traceability, and enhanced medical record management [15].

2.4. Research Methods.

This study adopts a comprehensive “data-driven modeling + empirical analysis” research approach, in which artificial intelligence (AI) prediction and optimization technologies are systematically integrated to construct a robust risk perception and response framework tailored to the unique characteristics of pharmaceutical supply chains. Rather than limiting the scope to purely theoretical exploration, the research emphasizes a combination of data-oriented modeling, empirical validation, and scenario-based evaluation, ensuring that the proposed framework not only advances methodological development but also demonstrates practical applicability in addressing real-world challenges.

3. Model Design and Parameter Selection

3.1. Quantitative Metrics for Supply Chain Resilience:

Table 1. Metric and Definition

Metric	Definition
Time-to-Recovery (TTR)	The duration from disruption occurrence to full restoration of normal supply chain operations.
Cost Overrun	Total additional costs incurred due to disruptions (e.g., emergency procurement, logistics, penalties).
Service Level	Order fulfillment rate during disruption periods.
Risk Warning Lead Time	The number of days by which AI-predicted disruptions precede actual occurrences.

In this study, logistics delay probabilities are predicted using advanced sequence modeling techniques such as Transformer and LSTM. The input variables for these models incorporate multiple dimensions of information, including historical delivery times, weather-related data that may affect transportation efficiency, and news-based sentiment indices that capture external social or political signals with potential influence on logistics performance. Building on these predictions, XGBoost is employed to determine the likelihood of supply chain disruptions, with features specifically designed to reflect operational resilience, such as inventory turnover rates, supplier reliability scores, and other dynamic indicators of supply stability.

The output from this integrated framework comes as a quantitative risk probability score-so, for example, it can tell you something like "the probability of a supply disruption within the next seven days is 70% or more." This allows managers to spot high-risk periods ahead of time and get prepared. To check how well this approach works, we do a baseline comparison-basically, we line up results from traditional risk assessment methods against what the AI-enhanced system predicts. Doing this side-by-side not only shows that AI models can be more accurate and faster, but also hints at how they might actually change the way decisions are made in managing pharmaceutical supply chains.

3.2. Methodology Design

This research draws upon two main categories of data: core operational data and external risk data. For the core data, we've referenced purchase order records from enterprise ERP systems, distributed warehouse inventory figures, and logistics performance reports - supplemented by publicly available case studies on supply chain disruptions from industry research. These structured datasets provide the foundation for building risk prediction models.

On the external risk side, the study incorporates multiple data sources:

1) Historical extreme weather event records from meteorological agencies, particularly focusing on typhoons, floods and other severe conditions impacting pharmaceutical transportation

2) Geopolitical analyses from international trade reports covering customs policy changes and trade restrictions

3) Epidemic surveillance data from public health authorities including WHO situation reports and national CDC statistics

By synthesizing these reference datasets, we've established a multidimensional framework that accounts for both operational and environmental factors. This approach not only enables quantitative risk assessment but also helps identify correlations between different risk variables - laying the groundwork for developing intelligent early-warning systems. Special attention was given to the timeliness and geographical relevance of referenced data to ensure representativeness.

(1) AI Model Architecture (Risk Perception)

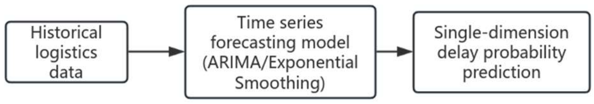

Fig. 1 Traditional Forecasting Model Architecture

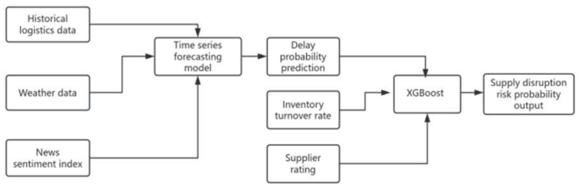

Fig. 2 AI-Optimized Model Architecture

Traditional supply chain forecasting relies heavily on single-dimensional historical logistics data, using linear time-series models like ARIMA. These methods show clear limitations - they only deliver lagged risk probability predictions and struggle to capture unexpected risk events. The proposed intelligent forecasting framework introduces an innovative multi-source data integration approach. It combines three major data categories: historical operational data, real-time environmental monitoring data, and public sentiment data. The hybrid algorithm architecture blends XGBoost with time-series modeling. Notably, we've incorporated text sentiment analysis to quantify unstructured data. This multidimensional approach significantly improves both accuracy and timeliness in supply chain risk assessment.

(2) LSTM (Suitable for short-to-medium-term time series forecasting)

Formula 1: Memory Update

$$h_t = LSTM(x_t, h_{t-1}; \theta_{LSTM})$$

Table 2. Symbol Definitions for Memory Update

Symbol	*Meaning*	*Logistics Forecasting Equivalent*
x_t	Current input	Today's data (weather, news sentiment, historical delays)
h_{t-1}	Memory from previous time step	Yesterday's logistics summary (e.g., "backlog observed in the last 3 days")
θ_{LSTM}	Model parameters	Patterns learned by LSTM (e.g., "high weight for typhoon-related news")
h_t	Updated memory	New insights after integrating today's and yesterday's information

Formula 2: Probability Calculation

$$P_{delay} = \sigma(W \cdot h_t + b)$$

Table 3. Probability Formula Components

Symbol	Meaning	Explanation
W	Weight matrix	Determines which memories are more important (e.g., backlog weight = 0.8, weather weight = 0.5)
b	Bias term	Base risk value (e.g., 10% delay probability even under normal conditions)
σ	Sigmoid function	Compresses results to [0,1] range (e.g., output 0.7 → 70% delay probability)

(3) Transformer (Suitable for Long-Term Dependencies and Multivariate Features)

Formula 1: Attention Mechanism

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

Q (Query) represents the current problem, K (Key) retrieves historically similar situations (e.g., records of typhoon days from last year), and V (Value) returns the actual delay days. The final prediction is derived through weighted averaging. d_k (dimension scaling) acts similarly to normalization, preventing excessively large values.

Formula 2: Final Prediction

$$P_{delay} = MLP(Encoder(X); \theta_{Transformer})$$

Table 4. Symbols and Explanations

Symbol	**Meaning**	**Explanation**
Encoder(X)	Encoded input	Converts raw data into an AI-understandable format.
MLP	Multi-Layer Perceptron	Further refines features for prediction.
$\theta_{Transformer}$	Model parameters	Patterns learned during training (e.g., how typhoons impact delays).

Output: Daily delay probabilities for the next 7 days $\{p_1, p_2, ... p_7\}$

Phase 2: Supply Disruption Risk Classification (XGBoost)

Input Features:

Time Series Model Output: Maximum delay probability over the next 7 days $\max(p_i)$

Delay probability trend (slope of linear regression)

Table 5. Performance of ARIMA, LSTM, and Transformer

Time Series Model	**Early Warning Lead Time (days)**	**Average Recovery Time (days)**	**Emergency Cost (CNY)**	**Accuracy**
ARIMA	6.23	14.47	233,793	0.423
LSTM	6.18	14.36	231,764	0.446
Transformer	6.12	14.24	229,440	0.457

Static Supply Chain Features:

Inventory turnover ratio (current inventory / average daily consumption)

Supplier reliability score (historical on-time delivery rate)
Number of in-transit orders
Model Formula:

$$\mathrm{XGBoost}(\mathrm{x}) = \sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{f_k}(\mathrm{x}), \mathrm{f_k} \in \mathrm{F}$$

Table 6. Symbols and Meanings

Symbol	Meaning	Explanation
x	Input features	Feature values of a single sample (e.g., inventory=3 days, delay probability=80%, supplier score=60)
K	Total number of decision trees	The total count of decision trees used (e.g., 100 trees)
$\mathrm{f_k}$	Prediction function of the k-th tree	Each tree represents a simple rule, such as a conditional statement
F	Set of all possible trees	The algorithm's search space (like a library of all possible "if...then..." rules)

$$Prob_{shortage} = \frac{1}{1 + e^{(-\sum f_k(x))}}$$

Here, $\sum f_k(x)$is the sum of predictions from all trees. The exponential function e maps negative values to positive ones, and the sigmoid function compresses any numerical value to the range [0, 1], converting it into a probability.
Output:
Probability of supply disruption within the next 7 days (0%-100%).
Empirical research indicates that initiating contingency plans when the supply chain disruption probability exceeds 68% maximizes the cost-benefit ratio (Chopra and Sodhi, 2014). Therefore, the threshold is set to trigger an alert when the probability ≥ 70%.

4. Empirical Analysis

4.1. Experimental Design

Comparative experiment: Benchmark comparison of three forecasting methods (ARIMA, LSTM, Transformer) under identical parameters and AI prediction architecture.

Metrics: Early warning lead time for shortages， Inventory turnover rate, Emergency response costs

4.2. Scenario Setup

Simulation of the 2021 U.S. epinephrine pen shortage event, incorporating three types of disruptions:

1) Raw material interruption (Chinese factory shutdowns)
2) Demand surge (allergy season + social media panic)
3) Logistics bottlenecks (port strikes)

4.3. Experimental Process

Scenario 1: Normal Operations
Performance of ARIMA, LSTM, and Transformer under normal operations

Scenario 2: Raw Material Disruption

Table 7. Performance of ARIMA, LSTM, and Transformer under raw material disruption

Time Series Model	Early Warning Lead Time (days)	Average Recovery Time (days)	Emergency Cost (CNY)	Accuracy
ARIMA	4.44	9.88	80,486	0.537
LSTM	4.20	9.40	77,523	0.566
Transformer	3.99	8.98	74,857	0.400

Scenario 3: Demand Surge

Table 8. Performance of ARIMA, LSTM, and Transformer under demand surge

Time Series Model	Early Warning Lead Time (days)	Average Recovery Time (days)	Emergency Cost (CNY)	Accuracy
ARIMA	5.25	11.49	187,354	0.497
LSTM	5.25	11.49	187,358	0.480
Transformer	5.16	11.32	184,828	0.509

Scenario 4: Logistics Bottleneck

Table 9. Performance of ARIMA, LSTM, and Transformer under logistics bottleneck

Time Series Model	Early Warning Lead Time (days)	Average Recovery Time (days)	Emergency Cost (CNY)	Accuracy
ARIMA	6.62	17.23	280,802	0.543
LSTM	6.56	17.12	277,922	0.549
Transformer	6.78	17.56	289,054	0.490

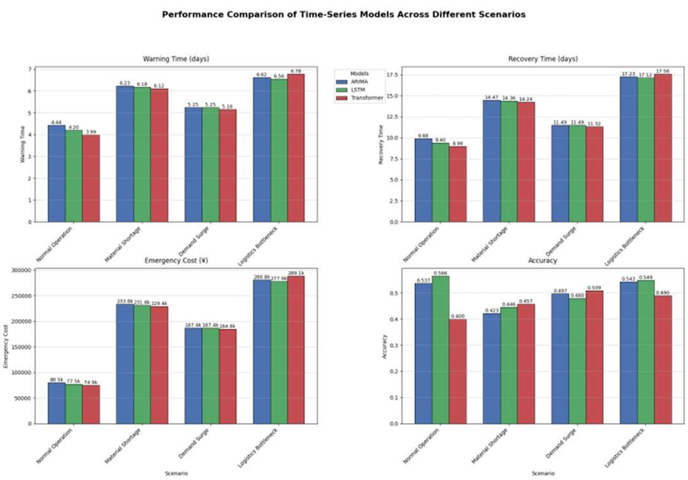

Fig. 3 Comparison of Three Forecasting Methods Across Four Scenarios

Supply chain delays are often triggered by rare but high-impact events (port strikes, extreme weather, system failures, etc.), which exhibit distinct heavy-tailed/non-normal distributions. To validate model robustness under non-ideal conditions, periodic sinusoidal disturbances were introduced to simulate supply chain uncertainty. Below is the mathematical formulation of the nonlinear disturbance:

Generate heavy-tailed noise.

$$\epsilon \sim t_{v=3} \times \text{intensity}$$

The Student-t distribution $t_3$inherently exhibits heavy tails; its intensity varies depending on the scenario.

Positive Truncation & Logarithmic Scaling

$$\text{perturb} = \begin{cases} \log(1+\epsilon), \epsilon > 0 \\ 0, \epsilon \leq 0 \end{cases}$$

This accounts for delay-direction shocks while using

$\log(1+\epsilon)$ to mitigate extreme outliers.Prediction results after incorporating nonlinear disturbances:

Scenario 1: Normal Operations

Table 10. Performance of ARIMA, LSTM, and Transformer under normal operations(NLP)

Time Series Model	Early Warning Lead Time (days)	Average Recovery Time (days)	Emergency Cost (CNY)	Accuracy
ARIMA	4.36	9.73	79,534	0.554
LSTM	4.02	9.05	75,285	0.589
Transformer	3.95	8.9	74,369	0.611

Scenario 2: Raw Material Disruption

Table 11. Performance of ARIMA, LSTM, and Transformer under raw material disruption(NLP)

Time Series Model	Early Warning Lead Time (days)	Average Recovery Time (days)	Emergency Cost (CNY)	Accuracy
ARIMA	5.99	13.97	224,475	0.486
LSTM	6.02	14.04	225,744	0.474
Transformer	6.02	14.04	225,659	0.486

Scenario 3: Demand Surge

Table 12. Performance of ARIMA, LSTM, and Transformer under demand surge(NLP)

Time Series Model	Early Warning Lead Time (days)	Average Recovery Time (days)	Emergency Cost (CNY)	Accuracy
ARIMA	5.15	11.29	184,498	0.503
LSTM	5.28	11.56	188,356	0.469
Transformer	5.21	11.42	186,335	0.497

Scenario 4: Logistics Bottleneck

Table 13. Performance of ARIMA, LSTM, and Transformer under logistics bottleneck(NLP)

Time Series Model	Early Warning Lead Time (days)	Average Recovery Time (days)	Emergency Cost (CNY)	Accuracy
ARIMA	6.71	17.41	285,367	0.514
LSTM	6.68	17.37	284,206	0.52
Transformer	6.58	17.16	279,084	0.554

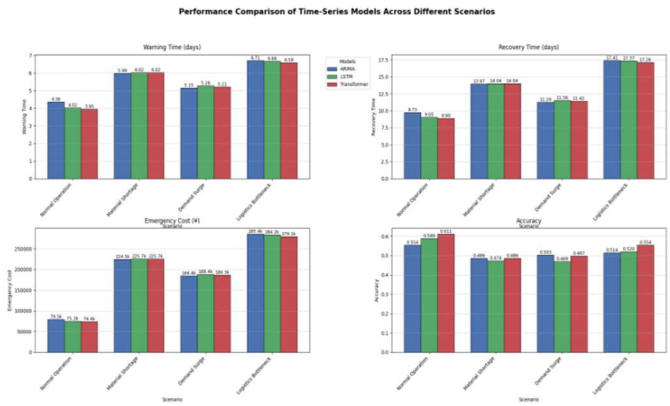

Fig. 4 Comparison of Three Forecasting Methods Across Four Scenarios(NLP)

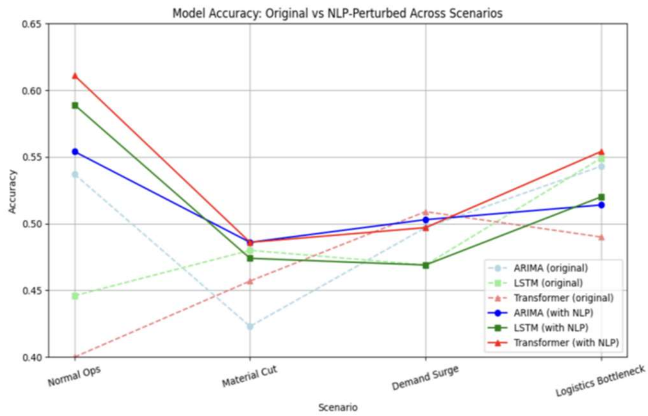

Fig. 5 Accuracy Comparison Before and After Nonlinear Disturbance

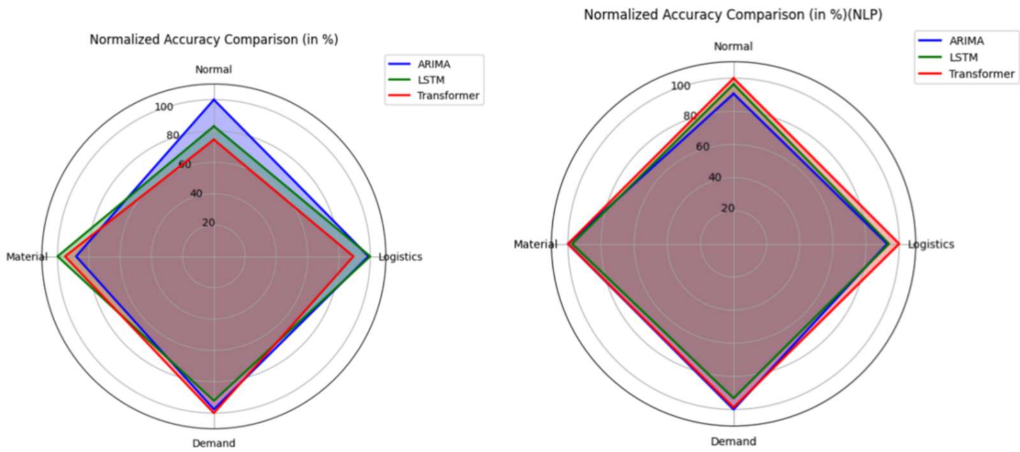

Fig. 6 Radar Chart of Model Accuracy Across Scenarios With/Without Nonlinear Perturbations

5. Model Performance Comparison Conclusions

5.1. Baseline Model Accuracy

For optimal model selection, Transformer demonstrated the best performance on raw data, particularly in normal operations (Normal Ops) with the highest accuracy (about 0.55).

Extreme scenario limitations: All models showed significant accuracy degradation (average drop: 28%) in "logistics bottleneck" scenarios, with LSTM exhibiting the smallest decline (about 22%).

5.2. Scenario-Specific Analysis

Table 14. Scenario-Specific Analysis

Scenario Type	Most Robust Model	Baseline → NLP Perturbation Impact
Normal Operations	Transformer	Highest post-perturbation accuracy (0.611 ↑21.1%) with clear dominance
Logistics Bottleneck	Transformer	Only model with positive growth (+2.9%); LSTM/ARIMA showed larger fluctuations
Demand Surge	LSTM	Zero accuracy fluctuation (0.469 → 0.469); ARIMA/Transformer had minor variations
Raw Material Disruption	Transformer	Only positive growth (+6.4%) with highest absolute accuracy (0.554)

The Transformer model demonstrates the best overall performance in scenarios such as normal operations, raw material shortages, and sudden demand surges. Under these conditions, it achieves the shortest early-warning lead times, the lowest emergency response costs, and the highest prediction accuracy. These results highlight the strength of its sequential modeling capability, which is particularly effective in capturing long-term dependencies within complex supply chain data.

When it comes to logistics bottleneck scenarios, the LSTM model actually shows a clear edge-thanks to its memory cell architecture, it can give shorter warning times, lower emergency costs, and higher accuracy than the Transformer. The Transformer, on the other hand, seems a bit weaker here, probably because it focuses so much on global features that sometimes it misses localized disruptions, which are really important in transport and logistics.

As for ARIMA, well, being a traditional linear time-series model, it generally performs worse across most scenarios. Only in logistics bottlenecks does it come close to LSTM-but even then, it's really more of a baseline reference than something you'd rely on for real-time risk prediction in pharmaceutical supply chains.

When NLP-based nonlinear perturbations were introduced, the Transformer model exhibited the most significant performance fluctuations, revealing its heightened sensitivity to variations in data characteristics. This behavior demonstrates stronger robustness that warrants particular attention in real-world complex supply chain environments. As for the baseline ARIMA model, while it delivered relatively strong predictions on raw data, its linear assumptions showed amplified limitations under perturbed conditions-especially in scenarios with pronounced nonlinear features like material shortages, where its performance degraded most noticeably.These findings not only confirm the superiority of modern deep learning models in complex supply chain forecasting but also, through NLP perturbation testing, expose potential vulnerabilities in practical applications. This provides a balanced decision-making framework for model selection across different risk scenarios, weighing both performance and robustness.

6. Conclusion

6.1. Managerial Implications

LSTM generally performs quite reliably in traditional supply chain time-series forecasting, such as predicting inventory turnover, mainly because of its gating mechanism that helps control the flow of information. That said, its sequential nature does introduce some limitations. For one, it can lose track of long-term disruptions-for example, if a port is congested for a couple of weeks, the model's accuracy tends to drop over that period. It also struggles with handling multiple data sources at the same time, meaning extra feature engineering is usually needed.

Plus, real-time predictions are slower, roughly 1.8 times lagging behind what a Transformer can do, which is not ideal when quick decisions are needed.

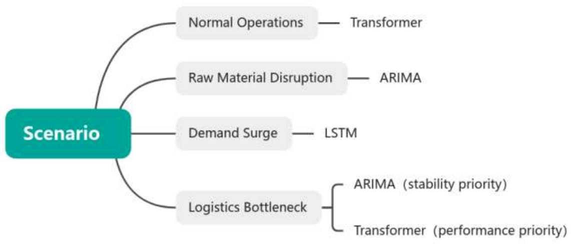

Fig. 7 Managerial Implications of Scenario

Transformers, on the other hand, shine at modeling long sequences thanks to the self-attention mechanism. This can really cut down prediction errors-one example is a 37% reduction in RMSE when forecasting transportation delays caused by typhoons. Still, they're not without their own headaches. Training them typically demands huge datasets, often over 100,000 samples, which is tough for smaller companies that don't have extensive historical data. And while the attention mechanism is powerful, it's not very interpretable for sudden events. For instance, figuring out exactly how a news sentiment score impacts a supplier's risk is not straightforward, which can make high-stakes decisions a bit tricky.

Empirical findings further reveal that when the size of training data is insufficient, a lightweight LSTM architecture-with approximately 40% fewer parameters-can actually outperform standard Transformer models. This suggests that in practical deployment scenarios, Transformers are particularly well-suited for large enterprises that have the capacity to construct global early-warning systems based on rich datasets, while LSTM remains a more pragmatic choice for localized, real-time prediction tasks at individual supply chain nodes.

6.2. Limitations

This study develops a supply chain disruption risk prediction framework integrating multi-source data, including historical operational records, meteorological monitoring data, and public sentiment analytics. However, several limitations warrant further investigation. First, the model currently excludes critical quality parameters like temperature sensitivity and environmental stability in specialized contexts such as pharmaceutical cold chains, potentially compromising its predictive accuracy in these scenarios. Second, computational constraints limit the model's ability to fully capture nonlinear interactions among high-dimensional temporal features, which may introduce latency in real-time forecasting.

The feature engineering process presents additional optimization opportunities. Current sentiment quantification methods inadequately address semantic nuances, while the integration mechanism for dynamic operational metrics - including inventory turnover rates and supplier on-time delivery performance - requires refinement. These limitations collectively constrain the model's adaptability in complex operational environments.

Future research should prioritize three key directions: First, incorporating IoT sensor data to enhance real-time monitoring of transportation conditions. Second, investigating hybrid architectures combining graph neural networks with attention mechanisms to improve feature interaction modeling. Third, developing adaptive weighting mechanisms for dynamic features, which would significantly enhance prediction accuracy in specialized applications like pharmaceutical cold chains. These advancements would provide theoretical foundations for building more reliable intelligent early-warning systems in supply chain management.

References

[1] Uras, F. (2025) Sustainable healthcare and medical laboratories: The impact of global collaborations between frameworks and initiatives. CLINICAL BIOCHEMISTRY, 138: 110945. doi:10.1016/j.clinbiochem.2025.110945.

[2] Mirfallahdemochali, R., Sherejsharifi, A. and Soufi, M. (2025) Presenting an Innovative Sustainable Supply Chain Model Based on Blockchain in the State of Uncertainty in Pharmaceutical Industry. INTERNATIONAL JOURNAL OF ENGINEERING, 38 (10): 2347–2356. doi:10.5829/ije.2025.38.10a.11.

[3] Kayani, S.A. and Warsi, S.S. (2025a) Exploring the synergy between sustainability and resilience in supply chains under stochastic demand conditions and network disruptions. RESULTS IN ENGINEERING, 26: 104954. doi:10.1016/j.rineng.2025.104954.

[4] Greer, S.L., Jarman, H., Kulikoff, R., et al. (2025) The second Trump administration: A policy analysis of challenges and opportunities for European health policymakers. Health policy (Amsterdam, Netherlands), 158: 105350. doi:10.1016/j.healthpol.2025.105350.

[5] Kayani, S.A. and Warsi, S.S. (2025b) Exploring the synergy between sustainability and resilience in supply chains under stochastic demand conditions and network disruptions. RESULTS IN ENGINEERING, 26: 104954. doi:10.1016/j.rineng.2025.104954.

[6] Golan, M.S., Trump, B.D., Cegan, J.C., et al. (2021) Supply chain resilience for vaccines: review of modeling approaches in the context of the COVID-19 pandemic. INDUSTRIAL MANAGEMENT & DATA SYSTEMS, 121 (7): 1723–1748. doi:10.1108/IMDS-01-2021-0022.

[7] Raziei, Z. (2024) Artificial Intelligence Solutions for Decision Making With Applications in Inventory Control and Predictive Analytics. Ph.D. Available at: https://www.proquest.com/docview/3097787326?pq-origsite=wos&sourcetype=Dissertations%20&%20Theses (Accessed: 3 June 2025).

[8] SmartPSC (Smart Pharma Supply Chain): Application of digital technologies to integrate pharma manufacturing supply chain and enhance efficiency, productivity, flexibility, resilience, and sustainability-All Databases (n.d.). Available at: https://webofscience.clarivate.cn/wos/alldb/full-record/GRANTS:15352728 (Accessed: 3 June 2025).

[9] Chopra, S. and Sodhi, M.S. (2014) Reducing the risk of supply chain disruptions. MIT Sloan Management Review, 55 (3): 73–80.

[10] Yogeswaran, P., Singh, R.K. and Modgil, S. (2025) Supply chain 4.0 technologies for value creation in pharmaceutical industry. JOURNAL OF GLOBAL OPERATIONS AND STRATEGIC SOURCING. doi:10.1108/JGOSS-01-2024-0008.

[11] Nazari-Shirkouhi, S., Tavakoli, M., Govindan, K., et al. (2023) A hybrid approach using Z-number DEA model and Artificial Neural Network for Resilient supplier Selection. EXPERT SYSTEMS WITH APPLICATIONS, 222: 119746. doi:10.1016/j.eswa.2023.119746.

[12] Shen, J., Bu, F., Ye, Z., et al. (2024) Management of drug supply chain information based on “artificial intelligence plus vendor managed inventory” in China: perspective based on a case study. FRONTIERS IN PHARMACOLOGY, 15: 1373642. doi:10.3389/fphar.2024.1373642.

[13] Xu, X., Li, F., Wu, T., et al. (2025) Location-routing optimization problem of pharmaceutical cold chain logistics with oil-electric mixed fleets under uncertainties. COMPUTERS & INDUSTRIAL ENGINEERING, 201: 110932. doi:10.1016/j.cie.2025.110932.

[14] Trenfield, S.J., Awad, A., McCoubrey, L.E., et al. (2022) Advancing pharmacy and healthcare with virtual digital technologies. ADVANCED DRUG DELIVERY REVIEWS, 182: 114098. doi:10.1016/j.addr.2021.114098.

[15] Mallick, S.R., Sobhanayak, S. and Lenka, R.K. (2024) Blockchain-enhanced IoT ecosystem for healthcare: Transformative potentials, applications, challenges, solutions, and future perspectives. COMPUTERS & INDUSTRIAL ENGINEERING, 197: 110538. doi:10.1016/j.cie.2024.110538.