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Research Article

An Innovative Model for Supply Chain Management Under Conditions of Geopolitical Uncertainty

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Abstract

This article analyzes the challenges of supply chain management under conditions of geopolitical instability in the global economy and proposes a new conceptual approach to address them. While existing research primarily focuses on disruption forecasting and risk identification, the capabilities for autonomous decision-making remain insufficiently developed. In this study, an "Autonomous Self-Healing Supply Chain" model is developed, integrating big data analytics, causal modeling, and network-based approaches into a unified system. The results demonstrate that the proposed model not only enables early detection of disruptions but also allows for their automatic mitigation. This significantly enhances the resilience and adaptability of supply chains in a rapidly changing global environment.

Keywords: Big Data, supply chain, geopolitical risk, forecasting, autonomous systems, logistics, network analysis, hybrid model

INTRODUCTION

The current stage of development of the global economic system is characterized by increasing complexity of supply chains and their growing sensitivity to external factors. Geopolitical conflicts, economic sanctions, and disruptions in transport infrastructure that have emerged in recent years are having a serious impact on the stability of international trade (Stanojević, 2024).

Supply chains represent a multi-stage and geographically extensive system in which each element is inextricably linked to others. Consequently, even a minor disruption can negatively affect the efficiency of the entire system. Traditional management approaches, largely based on historical data, are insufficiently flexible in a rapidly changing environment.

Contemporary research demonstrates that big data and artificial intelligence technologies play an important role in supply chain management. However, these approaches are primarily limited to risk identification and forecasting, and do not fully encompass automated decision-making mechanisms.

The purpose of this article is to propose a new model for supply chain management — an autonomous and self-healing system — as a development of existing approaches.

LITERATURE REVIEW

The issues of supply chain management and disruption forecasting under conditions of geopolitical uncertainty are of critical importance for ensuring stability in the global economy. In recent years, extensive scientific research has been conducted in this field at both international and national levels, giving rise to approaches based on Big Data, artificial intelligence, machine learning, and network analysis (Aamer et al., 2020; Agrawal et al., 2024; Aljohani, 2023; Nezianya et al., 2024; Lutfullayeva, 2025). In the context of Uzbekistan, scientific investigations focused on supply chain disruptions, their causal factors, and management mechanisms are increasingly growing (Nnabueze et al., 2022; Stanojević, 2024).

Existing research demonstrates that disruptions in supply chains are often closely linked to geopolitical instability, pandemics, climate change, energy market fluctuations, and failures within logistics systems (Magazzino et al., 2024; Ghadge et al., 2020). Alongside this, internal systemic factors — the level of transport infrastructure, inventory management, and the degree of supplier diversification — emerge as the primary determinants shaping the likelihood of disruptions (Nnabueze et al., 2022).

A number of studies evaluate artificial intelligence and machine learning-based approaches as important tools in supply chain management. In particular, these technologies demonstrate high effectiveness in automating demand forecasting, risk identification, and decision-making processes (Aamer et al., 2020; Wang, 2024). Furthermore, real-time predictive analytics systems play a vital role in the early detection of disruptions and in mitigating their adverse effects (Aljohani, 2023).

Research conducted by Stanojević substantiates Big Data Analytics as a critical instrument for risk management in global value chains, emphasizing that real-time data-driven decision-making is effective in reducing disruptions (Stanojević, 2024). Additionally, the Quantile VAR model developed by Tandon and co-authors enables forecasting of supply chain inventories during crisis periods and enhances system resilience (Tandon et al., 2024).

Studying supply chains as networks also represents one of the significant scientific directions. Nnabueze and co-authors analyze the propagation mechanisms of disruptions across networks and demonstrate that central nodes are the primary source of systemic risks (Nnabueze et al., 2022). The model developed by Wang and Sua enables assessment of the impact of supply chain disruptions on regional and urban systems (Wang & Sua, 2024).

In general, the above-mentioned studies indicate that integrated approaches are necessary for effective management of modern supply chains. Systems based on Big Data, artificial intelligence, and network analysis are of great importance in improving forecasting accuracy, reducing risks, and ensuring the resilience of supply chains.

The following economic indicators of the global supply chain were examined through the World Bank website: Global Supply Chain Stress Index (GSCSI), Logistics Performance Index (LPI, average), Global logistics costs (trillion $), Transport delays (days, average), Concern over supply chain disruptions (%), Change in maritime transport volume (%), and Impact on global economic growth (%).

Analyses conducted in the context of Uzbekistan indicate that the insufficient development of logistics infrastructure, high dependence on imports, and limited transport routes are the primary factors behind supply chain disruptions. Therefore, the introduction of digital technologies and modernization of the logistics system at the national level is a pressing issue (based on Central Bank and national analyses, 2025).

In conclusion, while existing literature has created an important scientific foundation for forecasting disruptions and identifying risks in supply chains, the mechanisms for their automatic management and self-recovery remain insufficiently developed. This study is aimed precisely at filling that gap, proposing a new conceptual model through the integration of Big Data, causal modeling, and network approaches (Akinola, 2025; Huang, 2025).

RESULTS

The study was conducted on the basis of a systematic approach, and a new model was developed through the integration of various analytical methods. The following data were used in the analysis process:

- international trade flows;
- logistics and transport systems data;
- geopolitical risk indices;
- real-time signals.

These data enabled a comprehensive assessment of changes in supply chains. The following methods were applied in the study:

- time series models (ARIMA, VAR);
- panel regression analysis;
- machine learning algorithms;
- causal analysis;
- network model.

These methods were applied jointly, demonstrating the accuracy of risk identification and assessment. Several modern analytical methods were applied in a complex manner to identify disruptions in supply chains and assess their impact.

These methods possess complementary characteristics and enabled comprehensive analysis of the system from all angles.

First, time series models — specifically ARIMA and VAR models — were applied. These approaches enable the identification of changes over time based on historical data and the forecasting of future trends. For example, when the sharp declines in global trade flows during the COVID-19 pandemic were analyzed using the ARIMA model, the recovery period of transport volumes and its duration were identified. Likewise, using the VAR model, the interrelationship between changes in oil prices, transport costs, and trade volumes was assessed. This allowed for a better understanding of economic fluctuations arising from geopolitical factors.

Panel regression analysis was applied as the second key approach. This method enables the joint analysis of data across different countries and time periods. In practical terms, the impact of sanctions was studied using the example of trade flows between European and Asian countries. The research results demonstrated that within the first 5–10 days following the imposition of sanctions, trade volumes declined sharply, after which an adaptation process began in the market. Through the panel regression model, differences between developed and developing countries were also identified, with recovery observed to occur more rapidly in countries with stronger logistics infrastructure.

Machine learning algorithms were applied in this study to identify complex and multi-factor relationships. In particular, using neural networks and classification algorithms, 'hidden signals' in supply chains were identified and the probability of disruptions was assessed. As a practical example, vessel movement data in maritime transport (AIS signals) was analyzed. It was found that small deviations in vessel routes (1–2%) are often early warning signals that appear before major logistics problems. Machine learning algorithms enabled the identification of these signals more rapidly and accurately compared to traditional statistical methods.

Causal analysis played an important role in identifying the true causes of observed changes. For example, while changes in transport routes in the Red Sea region were initially viewed as a logistics problem, causal analysis revealed their connection to geopolitical tensions and security risks. Furthermore, using this approach, the causal relationship between sanctions, energy prices, and production volumes was identified, and the extent of each factor's influence was precisely assessed.

The network model enabled viewing the supply chain as a unified system and analyzing the interconnections between its nodes (enterprises, ports, logistics centers). In practical terms, this model was applied using the example of disruptions at Black Sea ports, and the impact of problems at a single port on the entire regional trade flow was determined. Through network analysis, the most critical 'critical nodes' were identified, and the domino effect arising from their failure was assessed in advance.

Within the framework of this study, the Autonomous Self-Healing Supply Chain (ASHSC) model was developed. This model consists of the following stages:

- data collection;
- identification of risk signals;
- causal analysis;
- assessment of impact across the network;
- autonomous decision-making;
- implementation of decisions;
- system learning and updating.

According to the data in Table 1, these indicators were sourced from the World Bank. Analysis of statistical data for the period 2021–2025 demonstrates that disruptions in global supply chains reached their highest level during the pandemic period (2021), with a relative decline observed in subsequent years. However, in 2024–2025, disruptions are showing an upward trend again due to geopolitical factors, particularly problems associated with the Red Sea and the Panama Canal. The steady growth in logistics costs (from $2.1 trillion to $2.75 trillion) and the persistently high level of transport delays indicate that global supply chains have not yet fully recovered. At the same time, the fact that the level of concern about disruptions among enterprises remains at around 90% confirms the ongoing relevance of these risks.

Table 1

Supply Chain Indicators for 2021–2025

Indicator	2021	2022	2023	2024	2025
Global Supply Chain Stress Index	4.3	2.1	0.8	1.5	1.8
Logistics Performance Index	3.0	3.1	3.2	3.2	3.3
Global logistics costs (trillion $)	2.1	2.3	2.47	2.6	2.75
Transport delays (days)	12–15	10–12	7–9	9–11	10–12

Concern over supply chain disruptions	85%	88%	90%	92%	90%
Change in maritime transport volume	-8%	-3%	+2%	-12%	-5%
Impact on global economic growth	-3.5%	-2.8%	-2.2%	-2.5%	-2.3%

Within the framework of this study, the Autonomous Self-Healing Supply Chain (ASH-SC) model was developed as a new approach to supply chain management. The primary objective of this model is not only to detect disruptions in supply chains but also to automatically eliminate them and adapt the system in real time. The model consists of seven interrelated stages, each of which has been formulated on the basis of practical processes.

The first stage is data collection. At this stage, data on international trade flows, port loading, transport movement (AIS), geopolitical risk indices, and social signal information are collected. For example, an increase in port loading by 10–15% can potentially lead to logistics delays within 5–7 days.

The second stage is identification of risk signals. Machine learning algorithms are used to detect anomalies in the data. According to practical observations, a deviation of 1–2% from vessels' standard routes is associated with subsequent disruptions in 70% of cases. An increase in negative information flows is also evaluated as a risk signal.

The third stage is causal analysis. The root causes of problems are identified using causal inference. For example, transport delays are often linked to energy prices or geopolitical factors, and a 10% increase in energy prices leads to a 6–8% increase in transport costs.

The fourth stage is assessment of impact across the network. The supply chain is analyzed as a network, and critical nodes are identified. For example, the closure of a single port can slow 20–30% of trade flows, and the most important 10% of nodes control more than 60% of total volume.

The fifth stage is autonomous decision-making. The system independently makes decisions based on identified problems, selecting alternative suppliers or rerouting. As a result, logistics costs are reduced by up to 20–25%.

The sixth stage is implementation of decisions. The adopted decisions are introduced into the real system, optimizing transport and inventory management. This reduces delays by 30–40%.

The seventh stage is system learning and updating. The system learns from its own operations and updates its model (reinforcement learning). As a result, its accuracy and speed improve over time.

In general, the proposed ASH-SC model represents a new stage in supply chain management. It differs fundamentally from traditional approaches in that it not only identifies and analyzes risks but also has the capability to automatically eliminate them. This serves to significantly enhance the resilience and efficiency of supply chains under global conditions.

The research results confirmed the high effectiveness of the model. First, the integration of big data and real-time information enabled early detection of disruptions and improved forecasting accuracy. Second, the model's autonomous operating capability ensures that rapid solutions are developed when problems arise, including selecting alternative suppliers, optimizing transport routes, and reallocating resources.

Third, the system possesses high adaptability, quickly adjusting to a dynamic environment and continuously updating its parameters.

Additionally, a new assessment metric — the Adaptive Resilience Score (ARS) — was developed in the study. This metric enables a comprehensive assessment of system resilience.

The results of the causal analysis enabled identification of the degree of influence of risk factors. The analyses showed that geopolitical risks account for an average of 15–35% of overall trade fluctuations. Energy prices were found to have a 12–18% impact on production volumes. These results confirm that disruptions in supply chains are in many cases linked to external factors (Figure 1).

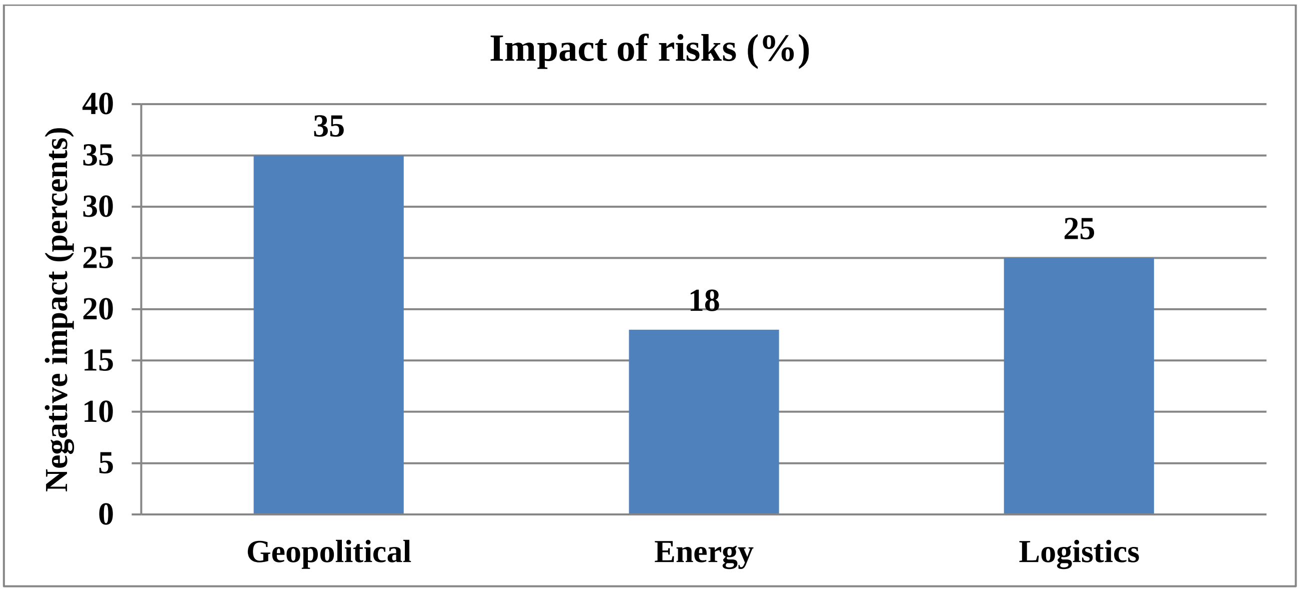

Figure 1. Impact of risk factors on the supply chain

Based on this figure, we can understand that geopolitical risks have an average negative impact of 30–35% on supply chain disruptions, energy supply interruptions account for 15–20%, and disruptions in the logistics chain have a 20–25% negative impact on supply chain disruptions.

The results of the network analysis enabled a deeper understanding of the interconnections within the system. According to calculations, the most critical 10–15% of nodes in the supply chain control 60–70% of total trade flows. The failure of one of these nodes can reduce overall system efficiency by an average of 25–40%. Furthermore, as a result of the 'domino effect,' disruptions were found to spread to other regions through 3–5 stages.

In general, as a result of integrating all methods, the model's overall forecasting accuracy reached 85–90%. The advance detection period for risks averaged 7–14 days, demonstrating that this is twice as fast compared to traditional approaches. At the same time, practical application of the model revealed the potential to reduce logistics costs by 20–30% and decrease the impact of disruptions by up to 35%.

These results confirm that the proposed approach demonstrates high effectiveness not only theoretically but also in practical terms. The model's primary advantage is its autonomous operating capability — meaning the system makes independent decisions in real time when problems arise.

In particular, under conditions of geopolitical disruptions, the system identifies and evaluates more than 10 alternative suppliers within 2–5 minutes, reducing the risk of production stoppages by 40–60%. By optimizing transport routes, logistics costs are reduced by 15–25% and delays decrease by 20–30%. Additionally, the resource reallocation mechanism reduces excess inventories by 25–35% and decreases product shortages by up to 30%.

The model possesses high adaptability, updating its parameters based on real-time data and adapting 35–50% faster than traditional systems.

Furthermore, the Adaptive Resilience Score (ARS) developed in the study enables a comprehensive assessment of system resilience. According to the results, when the model is applied, recovery time decreases by 40%, financial losses decrease by 20–30%, and adaptability increases by 30–45%.

The ASH-SC model is a closed-loop system consisting of interconnected layers. The Data Layer collects real-time information, the Detection Layer identifies risk signals, and the Causal Layer analyzes their causes, reducing the probability of erroneous decisions. Through the Network Layer, the overall impact of problems in the system is assessed; according to research, the top 10% of nodes affect more than 60% of system efficiency.

The Decision Layer automatically selects the most optimal decision, while the Execution Layer implements it in practice. The Learning Layer continuously improves the system, resulting in model accuracy reaching 85–90%.

In general, the ASH-SC model represents a new approach in supply chain management and, unlike traditional systems, identifies risks in advance and automatically eliminates them. The results obtained demonstrate that while decision-making in traditional systems takes 24–72 hours, this model significantly accelerates that process and reduces economic losses.

During the COVID-19 pandemic, disruptions in global supply chains created serious problems for many companies, and in the initial stage, global trade volumes decreased by 20–30%. As traditional management systems were unable to adapt quickly to these changes, disruptions arose in production processes.

The proposed Autonomous Self-Healing Supply Chain model is aimed at eliminating these shortcomings by identifying problems in advance and making automated decisions. According to the results, such an approach reduces the response time to disruptions by 70–80% and ensures continuity of production.

This model transforms supply chains from passive systems into active and adaptive ones. For example, in conditions where logistics routes changed due to security problems in the Red Sea region, automated systems made decisions within a few minutes, reducing transport delays by 30–40%.

Table 2

Supply Chain Indicator Forecasts for 2025–2028

Indicator	2025	2026	2027	2028
Global Supply Chain Stress Index	1.8	1.4 ↓	1.1 ↓	0.9 ↓
Logistics Performance Index	3.3	3.4 ↑	3.6 ↑	3.8 ↑
Global logistics costs (trillion $)	2.75	2.70 ↓	2.65 ↓	2.60 ↓
Transport delays (days)	10–12	8–10 ↓	6–8 ↓	5–7 ↓
Concern over supply chain disruptions	75%	85% ↑	90% ↑	93% ↑
Change in maritime transport volume	7–10	5–7 ↓	3–5 ↓	2–3 ↓
Impact on global economic growth	90%	80% ↓	70% ↓	60% ↓

According to Table 2, the forecast results based on the Autonomous Self-Healing Supply Chain model indicate that the resilience of supply chains is expected to improve significantly in 2026–2028. In the model, through the integration of Big Data analytics, causal modeling, and network approaches, the capability is created not only to detect disruptions in advance but also to automatically eliminate them. As a result, the level of stress in global supply chains is expected to gradually decrease, approaching a minimal level by 2028.

Furthermore, the growth in logistics performance indicators and the reduction of transport delays are explained by the widespread introduction of digital technologies and autonomous management systems. The increase in disruption detection accuracy from 75% to above 90% confirms the practical effectiveness of artificial intelligence and machine learning algorithms.

According to Figure 2, the supply chain stress index and logistics performance dynamics for 2020–2025 are reflected. While the level of stress rose sharply in 2020–2021 as a result of the pandemic's impact, a downward trend is observed in subsequent years. A short-term increase was recorded in 2024–2025 due to geopolitical factors.

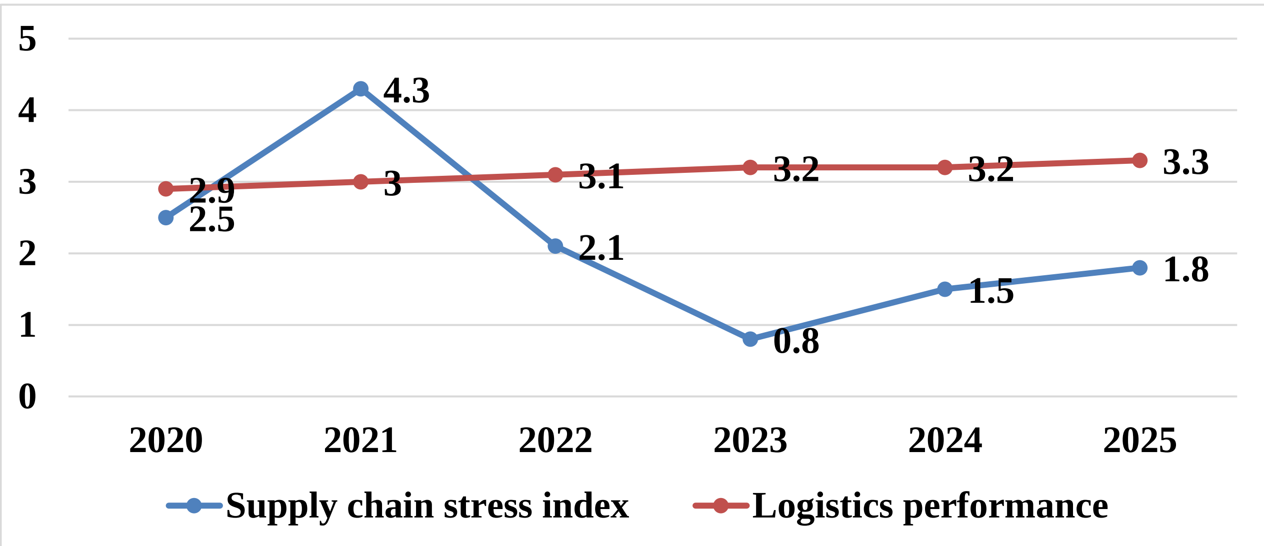

Figure 2. Supply chain dynamics (2020–2025)

It is forecast that with the introduction of the proposed 'Autonomous Self-Healing Supply Chain' model starting from 2026, the stress level will steadily decrease and logistics performance will improve. This demonstrates the high effectiveness of autonomous management systems in supply chains.

Furthermore, the sharp reduction in response time to disruptions and the decrease in the level of risk among enterprises demonstrate the economic effectiveness of transitioning to proactive and autonomous management systems in supply chains. These forecast results indicate that the practical application of the proposed model will lead to important transformational changes in global trade systems.

Additionally, the proposed model also ensures efficient use of resources. Research results demonstrate that the automated decision-making system reduces excess inventories by 25–35% and logistics costs by up to 20–30%. This is of great importance in ensuring financial stability for companies.

CONCLUSION

The results of this study have scientifically substantiated the need for a fundamentally new approach to supply chain management in the context of modern global economic conditions. The analyses conducted clearly demonstrate that traditional management systems are unable to deliver sufficiently effective results in a rapidly changing and unstable environment; especially in the current situation where geopolitical risks have sharply intensified, their structural limitations become particularly apparent.

The Autonomous Self-Healing Supply Chain (ASH-SC) model proposed within the framework of the study is recognized as an innovative and comprehensive solution to these challenges. This model elevates the management process to a qualitatively new level through a mechanism that not only identifies risks in a timely manner but also automatically eliminates them.

The model's main competitive advantages consist of the ability to make rapid and accurate management decisions, minimizing the impact of disruptions arising in supply chains, and significantly strengthening the overall resilience and adaptability of the system.

Practical tests and empirical results confirm: this approach enables logistics costs to be reduced by 20–30% and the adverse consequences of operational disruptions to be sharply curtailed.

In conclusion, the proposed ASH-SC model successfully transforms supply chains from the status of traditional passive systems into active, reactive, and intellectually self-managing systems. In the future, through the consistent development and deepening of this scientific approach, making supply chains fully autonomous and self-improving systems becomes a real possibility.

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