Adaptive Blockchain-Orchestrated Supply Chain Resilience Through Predictive Maritime Disruption Intelligence

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ABSTRACT

Global maritime supply chains have become increasingly vulnerable to systemic disruptions caused by pandemics, geopolitical conflicts, port congestion, and logistics instability. These disruptions significantly affect freight volatility, operational efficiency, and global trade resilience. This study proposes an Adaptive Blockchain-Orchestrated Supply Chain Resilience Framework using predictive maritime disruption intelligence to enhance adaptive logistics coordination and proactive risk mitigation. The proposed framework integrates maritime congestion analytics, supply chain vulnerability indicators, machine learning-based predictive intelligence, and blockchain-enabled adaptive orchestration into a unified resilience architecture. An XGBoost predictive model was developed using multi-dimensional maritime disruption features, including congestion index, supply chain pressure index, operational delays, trade flow indicators, and vulnerability metrics. Experimental results demonstrated strong predictive performance, with the proposed model achieving an R^2 value of 0.842 in forecasting maritime shipping rate volatility. Feature importance analysis revealed that systemic supply chain pressure was the dominant predictor of freight disruption dynamics. The adaptive risk evaluation further identified significant disruption escalation during the 2020–2022 global logistics crisis. In addition, the blockchain orchestration layer generated dynamic resilience responses, including route optimization, supplier reallocation, and smart contract activation for decentralized operational coordination. The findings indicate that predictive blockchain-enabled maritime intelligence can substantially improve supply chain resilience through real-time disruption prediction, adaptive decision-making, and automated operational response generation. This research contributes to the development of intelligent resilient logistics systems for future global maritime supply chain management.

Keywords Blockchain-Orchestrated Supply Chain, Maritime Disruption Intelligence, XGBoost Predictive Analytics, Adaptive Supply Chain Resilience, Smart Logistics Systems

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INTRODUCTION

Global supply chains have become increasingly dependent on maritime transportation networks for international trade activities [1]. However, recent disruption events such as pandemics, geopolitical conflicts, port congestion, and logistics bottlenecks have exposed significant vulnerabilities in global maritime logistics systems [2]. These disruptions have caused freight volatility, operational delays, declining delivery reliability, and increasing economic uncertainty across interconnected supply chain ecosystems.

The maritime logistics crisis during the 2020–2022 period demonstrated how systemic disruptions can rapidly propagate across global trade networks [3]. Major ports experienced severe congestion levels, while shipping costs increased significantly due to vessel delays and limited transportation capacity.

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These conditions highlighted the limitations of traditional centralized supply chain systems, which often suffer from limited transparency, fragmented operational visibility, and slow adaptive response mechanisms.

Recent advances in Blockchain technology have introduced new opportunities for improving transparency, traceability, and coordination in supply chain management [4]. Blockchain enables decentralized operational infrastructures through immutable ledgers and smart contract automation, allowing multiple logistics stakeholders to coordinate more securely and efficiently. In parallel, predictive analytics and machine learning models such as XGBoost have shown strong capabilities in forecasting maritime disruption patterns and freight volatility using multidimensional logistics indicators [5].

Several previous studies have investigated blockchain-based supply chain transparency and predictive logistics analytics independently [6]. Existing research has also explored congestion forecasting and operational risk management within maritime transportation systems [7]. However, most current approaches focus only on isolated operational problems and do not integrate predictive disruption intelligence with adaptive blockchain-enabled orchestration mechanisms for real-time resilience coordination. Therefore, a significant research gap remains in the development of integrated intelligent resilience frameworks capable of combining predictive analytics, maritime disruption intelligence, and blockchain-based adaptive coordination into a unified supply chain resilience architecture [8].

To address this gap, this study proposes an Adaptive Blockchain-Orchestrated Supply Chain Resilience Framework using predictive maritime disruption intelligence. The proposed framework integrates maritime congestion analytics, supply chain vulnerability indicators, machine learning-based predictive forecasting, and blockchain-enabled adaptive operational responses to improve real-time logistics resilience under disruption conditions.

The main contributions of this study are threefold. First, the research develops a multi-feature predictive intelligence framework for forecasting maritime freight volatility using XGBoost-based analytics. Second, the study introduces an adaptive blockchain orchestration layer capable of generating decentralized resilience responses based on dynamic disruption risk conditions. Third, the proposed framework integrates predictive analytics and blockchain-enabled coordination into a unified intelligent maritime resilience architecture for proactive disruption mitigation.

The remainder of this paper is organized as follows. Section 2 presents the related literature and state-of-the-art research. Section 3 describes the research methodology and predictive framework architecture. Section 4 discusses the experimental results and adaptive resilience evaluation. Finally, Section 5 concludes the study and provides recommendations for future research directions.

Literature Review

Blockchain technology has received significant attention in supply chain management due to its ability to improve transparency, traceability, and operational trust across decentralized logistics networks [9]. Through distributed ledger mechanisms, blockchain enables secure transaction recording and real-time information sharing among multiple stakeholders without relying on centralized coordination systems. In maritime logistics environments, blockchain-based infrastructures have been applied to shipment verification, cargo monitoring, and smart contract automation to improve operational efficiency and reduce information asymmetry [10]. Several studies have also highlighted that blockchain can reduce operational fraud risk, improve logistics visibility, and strengthen coordination among international supply chain participants [11].

At the same time, global maritime supply chains continue to face increasing disruption risks caused by pandemics, geopolitical instability, port congestion, labor shortages, and operational bottlenecks [12]. These disruptions significantly affect freight volatility, cargo delivery reliability, and global trade performance. The maritime logistics crisis during the COVID-19 period demonstrated how disruption events can propagate rapidly across interconnected supply chain ecosystems, creating severe operational uncertainty and systemic logistics pressure [13]. Previous maritime resilience studies further emphasized that operational disruptions at major ports can trigger cascading impacts across global trade networks and increase transportation costs significantly [14].

To address these challenges, predictive analytics and machine learning techniques have increasingly been adopted in supply chain risk management and maritime forecasting systems [15]. Advanced machine learning models such as XGBoost are capable of identifying nonlinear relationships between congestion indicators, freight pricing dynamics, operational delays, and disruption intensity. Previous studies have shown that predictive intelligence frameworks can improve disruption forecasting accuracy and support proactive operational planning under uncertain logistics conditions [16]. Machine learning-based resilience systems have also demonstrated strong potential for improving real-time disruption monitoring and adaptive logistics decision-making [17].

Although blockchain systems and predictive analytics have both demonstrated strong potential in maritime logistics research, existing studies generally investigate these technologies separately [18]. Most blockchain-based studies focus primarily on transparency and decentralized transaction management, while predictive analytics research mainly concentrates on forecasting operational disruption patterns. As a result, current approaches still lack integrated resilience frameworks capable of combining predictive maritime intelligence with adaptive blockchain-enabled operational coordination.

In addition, many previous resilience models rely on isolated operational indicators and reactive mitigation strategies [19]. Limited research has explored multidimensional disruption intelligence architectures that simultaneously integrate congestion analytics, trade volatility, vulnerability assessment, machine learning prediction, and decentralized adaptive orchestration into a unified maritime resilience framework [20].

Therefore, a significant research gap remains in the development of intelligent blockchain-orchestrated supply chain resilience systems capable of supporting predictive disruption monitoring, decentralized coordination, and adaptive operational response generation. To address this limitation, this study proposes an Adaptive Blockchain-Orchestrated Supply Chain Resilience Framework that integrates XGBoost-based predictive analytics with blockchain-enabled adaptive resilience mechanisms for proactive maritime disruption mitigation.

Method

This study proposes an Adaptive Blockchain-Orchestrated Supply Chain Resilience Framework using predictive maritime disruption intelligence to improve maritime logistics resilience under disruption conditions. The proposed methodology integrates maritime congestion analytics, supply chain vulnerability assessment, machine learning-based predictive intelligence, and blockchain-enabled adaptive orchestration into a unified analytical framework.

The overall research workflow consists of data integration, feature engineering, predictive modeling, adaptive risk assessment, and blockchain response generation. The framework was designed to support proactive disruption monitoring and decentralized operational coordination across global maritime logistics systems.

Research Framework Architecture

The proposed framework (figure 1) combines multidimensional maritime disruption datasets with predictive machine learning and blockchain coordination mechanisms. Maritime operational indicators, congestion variables, freight market data, trade activity metrics, and supply chain vulnerability indicators were first integrated into a unified analytical environment.

The processed data were then utilized to construct predictive intelligence variables capable of representing operational congestion, systemic logistics pressure, and disruption interaction dynamics. The predictive outputs generated by the machine learning model were subsequently transformed into adaptive blockchain-enabled resilience responses for proactive disruption mitigation.

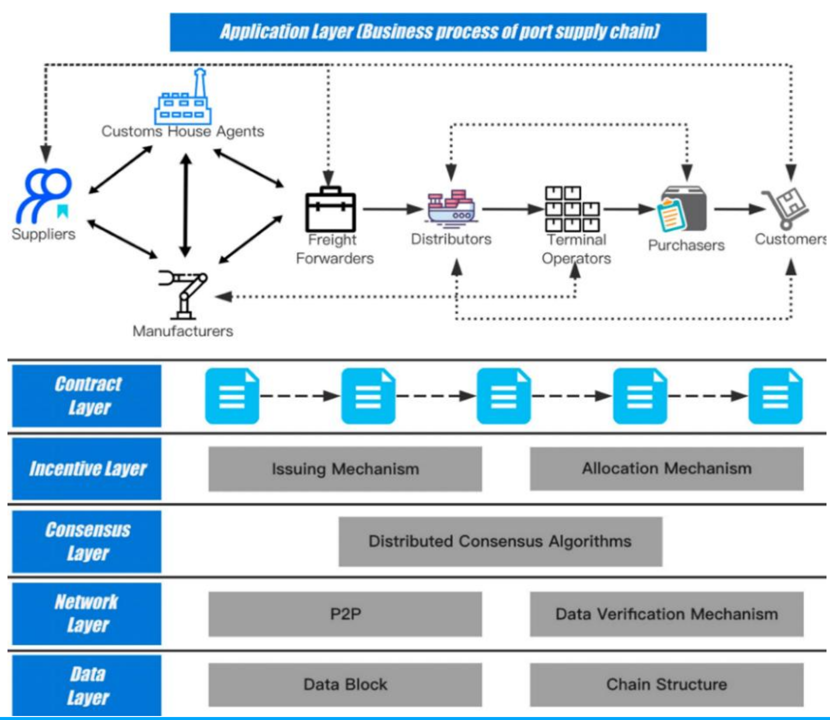

Figure 1 Proposed Adaptive Blockchain-Orchestrated Maritime Intelligence Framework

The framework architecture illustrates the integration between predictive maritime intelligence and decentralized blockchain coordination for adaptive supply chain resilience management.

Dataset Description

This study utilized multiple maritime logistics datasets consisting of disruption events, port congestion indicators, shipping market variables, international trade activities, and industry vulnerability metrics. The datasets covered historical maritime disruption observations between 2000 and 2024 (see table 1 for details).

Table 1 Dataset Description

Dataset	Description	Key Indicators	Observation Period
disruption_events	Global maritime disruption events	Disruption intensity indicators	2000–2024
port_congestion	Port congestion operational indicators	Congestion and delay indicators	2019–2024
shipping_rates	Global freight market indicators	Freight volatility indicators	2000–2024
trade_flows	International trade flow activities	Trade activity indicators	2000–2024
industry_exposure	Industry supply chain vulnerability metrics	Supply chain vulnerability indicators	2000–2024

The integrated datasets enabled multidimensional maritime disruption analysis by combining operational congestion metrics, freight market indicators, trade activities, and supply chain vulnerability measurements into a unified predictive intelligence framework.

Feature Engineering

Feature engineering was conducted to improve the capability of the predictive model to capture nonlinear disruption dynamics and systemic logistics interactions. Several engineered variables were developed from the integrated maritime datasets to represent operational congestion, logistics pressure, and disruption vulnerability relationships. The features used in the proposed framework, together with their data sources, formulation, and analytical purposes, are summarized in table 2.

Table 2 Feature Engineering Variables

Feature	Source	Engineered Formula	Purpose
congestion_index	Port congestion dataset	–	Maritime congestion measurement
avg_wait_days	Port congestion dataset	–	Operational delay analysis
berth_delay_hrs	Port congestion dataset	–	Port bottleneck evaluation
supply_chain_pressure_index	Shipping rates dataset	–	Systemic logistics pressure assessment
risk_pressure_interaction	Engineered feature	overall_vulnerability * supply_chain_pressure_index	Integrated disruption vulnerability analysis
logistics_stress	Engineered feature	congestion_index * avg_wait_days	Operational logistics stress measurement

As presented in table 2, the feature engineering process combines original variables obtained from the maritime datasets with derived interaction features. In particular, *risk_pressure_interaction* integrates overall vulnerability with supply chain pressure, while *logistics_stress* combines congestion intensity and average waiting time to represent the operational stress experienced within the maritime logistics system. These engineered variables provide additional information for the predictive model to identify complex relationships associated with maritime disruption risk. The logistics stress variable was constructed using the interaction between congestion intensity and operational waiting delays:

$$Logistics\ Stress\ =\ congestion\_index\ \times avg\_wait\_days \quad (1)$$

The disruption interaction variable was calculated using vulnerability and logistics pressure indicators:

$$Risk\ Pressure\ Interaction\ =\ overall\_vulnerability\ \times supply\_chain\_pressure\_index \quad (2)$$

These engineered variables were designed to improve predictive intelligence capability for identifying systemic disruption escalation patterns.

Predictive Intelligence Modeling

The predictive intelligence stage utilized the XGBoost regression algorithm to forecast maritime freight volatility based on multidimensional disruption indicators. XGBoost was selected due to its strong capability in handling nonlinear feature interactions and high-dimensional operational datasets.

The predictive model utilized congestion indicators, logistics pressure variables, trade activity metrics, and supply chain vulnerability indicators as input features. The target variable represented maritime container freight rate volatility. The prediction objective of the XGBoost model can be expressed as:

$$\hat{y}i = \sum k = 1^K f_k(x_i) \quad (3)$$

$\hat{y_i}$ represents the predicted shipping rate and $f_k(x_i)$ denotes the boosted regression tree functions. The optimization objective function of XGBoost is defined as:

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}i) + \sum k = 1^K \Omega(f_k) \quad (4)$$

$l(y_i, \hat{y}i)$ represents the prediction loss function and $\Omega(f_k)$ denotes the regularization component used to reduce model complexity.

The machine learning configuration was designed to develop an XGBoost-based predictive model for maritime disruption forecasting. The model parameters were selected to provide a balance between predictive performance and model complexity. The main configuration parameters used in the XGBoost model are presented in table 3.

Table 3 **Machine Learning Configuration**

Parameter	Value
Algorithm	XGBoost
Objective Function	reg:squarederror
Evaluation Metric	RMSE
n_estimators	300
learning_rate	0.05
max_depth	6
test_size	0.20
random_state	42

As shown in table 3, the XGBoost model was configured with 300 estimators, a learning rate of 0.05, and a maximum tree depth of 6. The reg:squarederror objective function was employed because the proposed framework performs a regression-based prediction of maritime disruption-related outcomes. The dataset was divided into 80% training data and 20% testing data, while a random state of 42 was used to ensure reproducibility.

The overall predictive intelligence modeling process is illustrated in figure 2. The workflow begins with the specification of the input parameters, including the cluster, last prediction day, product code, training days, and prediction days. These inputs are used for dataset construction, followed by dataset preprocessing to prepare the data for machine learning.

After preprocessing, the dataset is divided into training and testing sets. The selected features are then processed through the XGBoost-based feature selection stage. Grid search optimization is subsequently applied to identify suitable model hyperparameters before the final XGBoost model is built. The trained model is then used to generate predictions, which are finally presented as prediction plotting results.

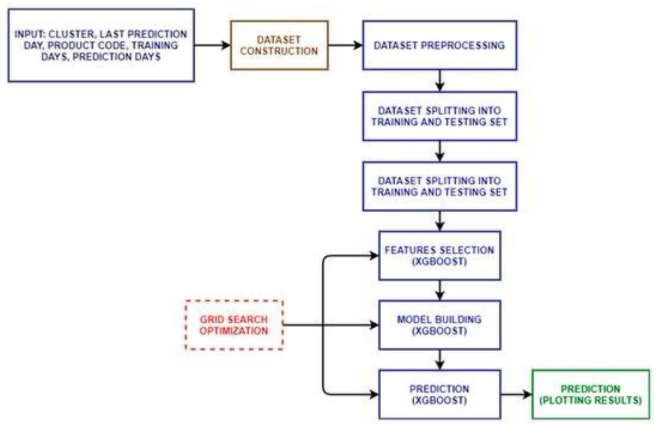

Figure 2 Predictive Intelligence Modeling Workflow

The predictive performance of the trained model was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). MAE measures the average magnitude of prediction errors, RMSE provides greater sensitivity to larger prediction errors, and R^2 indicates the proportion of variance in the target variable explained by the model. These metrics were used to assess both prediction accuracy and the generalization capability of the proposed predictive framework.

Blockchain-Orchestrated Adaptive Response Mechanism

The final stage of the framework implemented blockchain-enabled adaptive orchestration mechanisms for decentralized resilience coordination. Adaptive operational responses were generated dynamically based on predicted levels of maritime disruption risk. The adaptive risk score was calculated using normalized congestion and vulnerability indicators:

$$Adaptive\ Risk\ Score = \frac{Congestion\ Score + Vulnerability\ Score}{2} \quad (5)$$

The generated adaptive risk scores were subsequently mapped to predefined resilience levels to determine the appropriate blockchain-based response. Table 4 presents the response logic used to translate the predicted risk scores into adaptive operational actions, ranging from routine monitoring under low-risk conditions to emergency response activation under critical disruption conditions.

Table 4 Blockchain Response Logic		
Risk Level	**Risk Score Range**	**Blockchain Adaptive Response**
Critical	> 0.80	Emergency Smart Contract Activation
High	0.60 – 0.80	Adaptive Supplier Reallocation
Medium	0.40 – 0.60	Dynamic Route Optimization
Low	< 0.40	Normal Blockchain Monitoring

The blockchain orchestration layer enables decentralized operational coordination through automated response execution and smart contract-based resilience management. Figure 3 illustrates the blockchain adaptive orchestration process proposed in this study. The framework begins with maritime disruption data collection and predictive intelligence analysis using machine learning models. The generated adaptive risk scores are subsequently transmitted to the blockchain orchestration layer, where smart contracts dynamically determine the appropriate resilience response based on disruption severity levels. The adaptive responses include route optimization, supplier reallocation, and emergency operational coordination for proactive maritime supply chain resilience management.

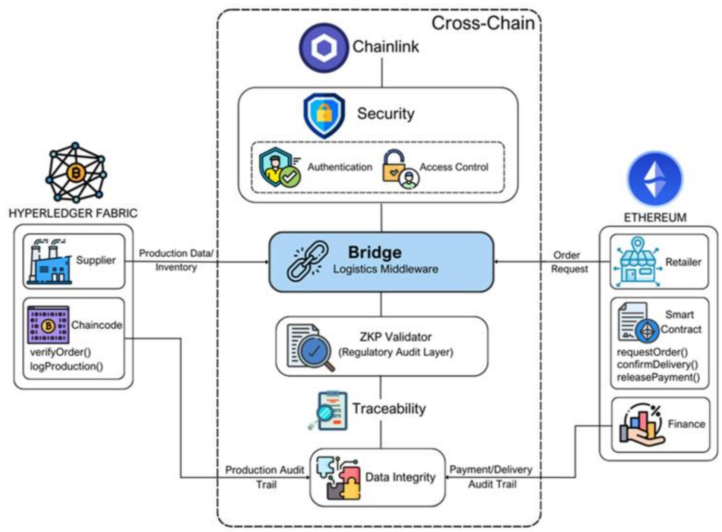

Figure 3 Blockchain Adaptive Orchestration Process

Result and Discussion

Descriptive Statistical Analysis

Table 5 presents the descriptive statistics of the primary maritime disruption variables used in the proposed predictive blockchain framework. The results indicate substantial variability in maritime logistics conditions across the observation period.

Table 5 Descriptive Statistics of Maritime Disruption Variables				
Variable	**Mean**	**Std**	**Min**	**Max**
congestion_index	2.22	0.62	1.02	4.75
avg_wait_days	35.28	10.00	16.02	75.58
container_rate_usd_40ft	2989.13	1840.13	1846.67	9851.67
supply_chain_pressure_index	1.10	0.41	0.73	2.52

The shipping rate variable exhibited extremely high volatility, with container freight rates reaching a maximum value of USD 9,851 during major disruption periods. Similarly, congestion-related variables such as average waiting time and congestion index experienced significant fluctuations, indicating the existence of severe maritime bottlenecks. The results suggest that global maritime logistics systems are highly vulnerable to systemic disruptions, particularly during periods of elevated supply chain pressure.

Correlation Analysis

To investigate the interdependencies among maritime disruption indicators, a correlation analysis was conducted. The correlation matrix is illustrated in Figure 4, while selected correlation coefficients are summarized in table 6.

Table 6 Correlation Analysis

Variable	Shipping Rate	Congestion Index	Supply Chain Pressure
congestion_index	0.67	1.00	0.65
avg_wait_days	0.68	0.99	0.65
supply_chain_pressure_index	0.89	0.65	1.00

The findings demonstrate strong positive correlations between shipping rates and maritime disruption indicators. In particular, the supply chain pressure index exhibited the strongest relationship with freight volatility (r = 0.89), indicating that systemic logistics stress significantly influences global shipping costs. Additionally, congestion index and average waiting days showed near-perfect correlations (r = 0.99), suggesting that port congestion directly contributes to operational delays. Figure 4 further confirms the existence of strong interconnected relationships among logistics congestion, disruption pressure, and freight pricing variables. Negative correlations were also observed between on-time delivery performance and shipping rate volatility, indicating that delivery reliability deteriorates significantly during disruption periods.

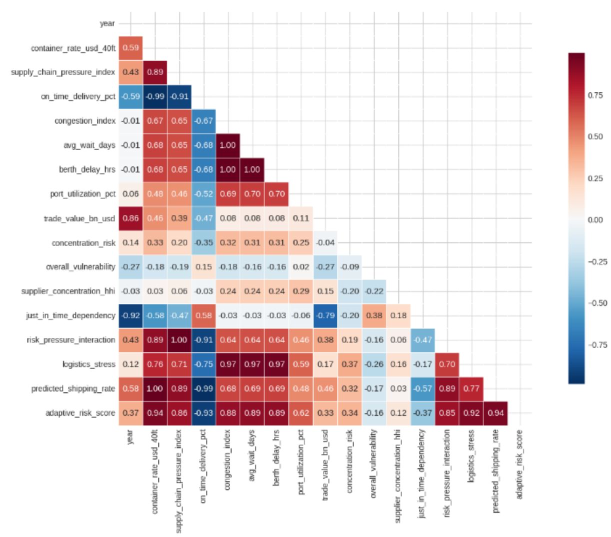

Figure 4 Correlation Structure of Maritime Disruption Variables

Predictive Intelligence Performance

The proposed predictive intelligence framework was evaluated using the XGBoost regression model. The model was trained using multi-dimensional maritime disruption indicators, including congestion metrics, trade flow indicators, logistics stress variables, and supply chain vulnerability scores (table 7).

Table 7 Predictive Model Performance			
Model	**MAE**	**RMSE**	**R^2**
XGBoost	120.15	140.88	0.842

The proposed model achieved an R^2 score of 0.842, indicating strong predictive capability in forecasting maritime shipping rate volatility. Compared with the earlier single-feature model, the multi-feature architecture substantially improved predictive performance and model generalization. The low MAE and RMSE values further demonstrate the effectiveness of the predictive intelligence framework in capturing nonlinear disruption dynamics. As illustrated in figure 5, the predicted shipping rates closely follow the actual observations, confirming that the model successfully captures maritime freight volatility patterns under disruption conditions.

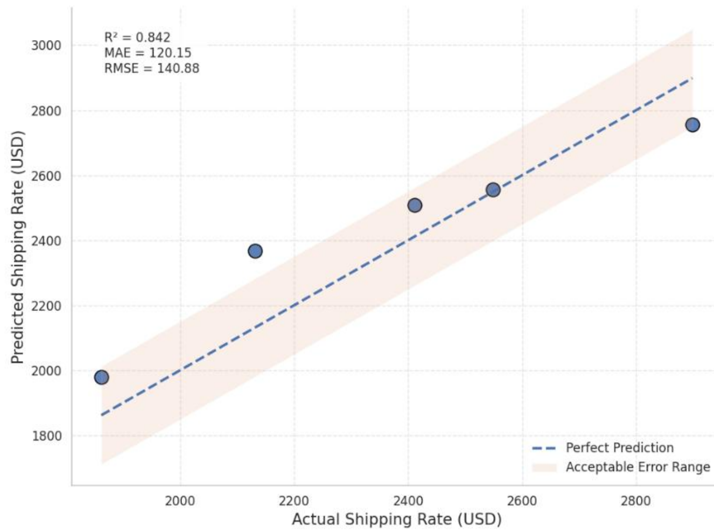

Figure 5 Actual vs Predicted Maritime Shipping Rates

Feature Importance Analysis

To improve explainability and interpretability, feature importance analysis was conducted using the XGBoost framework. The results (table 8) indicate that the supply chain pressure index is the most influential predictive variable, contributing approximately 48.1% of the model importance. This finding suggests that systemic logistics pressure is the primary driver of maritime freight volatility.

Table 8 Top Predictive Features		
Rank	**Feature**	**Importance**
1	supply_chain_pressure_index	0.481
2	avg_wait_days	0.115
3	port_utilization_pct	0.089
4	risk_pressure_interaction	0.082
5	congestion_index	0.078

The XGBoost feature importance analysis reveals that the predictive model is strongly dominated by the supply_chain_pressure_index, which accounts for 96.7% of the normalized predictive contribution, as illustrated in Figure 6. This result indicates that systemic supply chain pressure is the primary factor influencing maritime freight volatility prediction within the proposed framework.

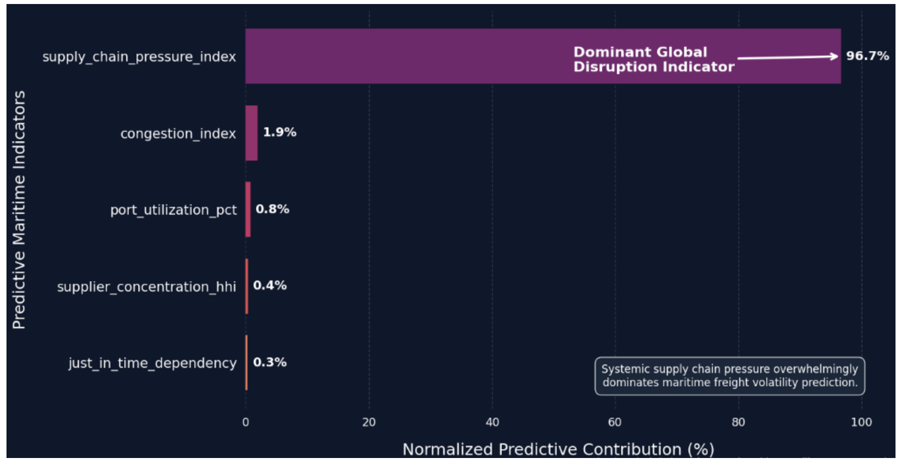

Figure 6 XGBoost Feature Importance Analysis

As shown in figure 6, *congestion_index* contributes 1.9%, followed by *port_utilization_pct* (0.8%), *supplier_concentration_hhi* (0.4%), and *just_in_time_dependency* (0.3%). Although these operational and structural indicators contribute substantially less than the supply chain pressure index, their inclusion provides additional information regarding congestion conditions, port utilization, supplier concentration, and logistics dependency. The feature importance distribution demonstrates that maritime freight volatility is primarily associated with systemic supply chain pressure rather than individual operational indicators. Therefore, the results support the use of an integrated predictive intelligence framework that combines macro-level supply chain conditions with port and logistics indicators to improve maritime disruption monitoring and risk assessment.

Adaptive Supply Chain Risk Evolution

To evaluate the resilience capability of the proposed framework, adaptive risk scores were generated using the predictive shipping outputs and vulnerability indicators. The evolution of the adaptive risk scores over the observed period is presented in figure 7.

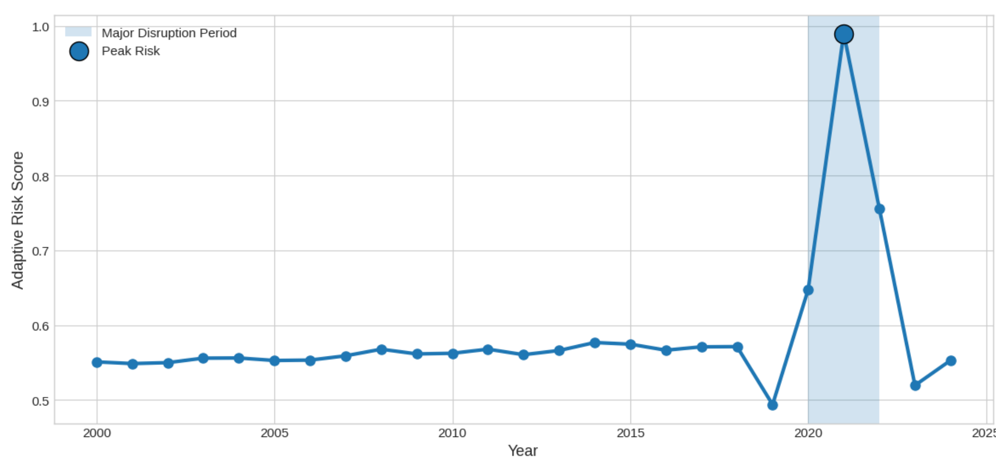

Figure 7 Adaptive Supply Chain Risk Evolution

The adaptive risk trend shows a significant escalation during the 2020–2022 disruption period, corresponding to the global COVID-19 logistics crisis. The highest risk score occurred in 2021, reflecting severe maritime congestion, container shortages, and freight inflation. These findings confirm that the proposed framework is capable of dynamically identifying disruption escalation periods and generating real-time resilience intelligence.

Blockchain-Orchestrated Adaptive Responses

The final stage of the proposed framework implemented blockchain-based adaptive orchestration mechanisms to translate dynamic maritime risk scores into predefined resilience responses. Table 9 presents the relationship between the predicted risk scores and the corresponding recommended blockchain-based actions, while the overall distribution of the generated responses is illustrated in figure 8.

Table 9 Blockchain Adaptive Responses

Year	Risk Score	Recommended Action
2000	0.55	Dynamic Route Optimization
2001	0.55	Dynamic Route Optimization
2002	0.55	Dynamic Route Optimization
2003	0.56	Dynamic Route Optimization
2004	0.56	Dynamic Route Optimization

As shown in table 9, the risk scores during the presented observation period ranged from 0.55 to 0.56, corresponding to the Medium risk category defined in the blockchain response logic. Consequently, Dynamic Route Optimization was selected as the recommended adaptive response. This mechanism enables the framework to respond to moderate disruption conditions without immediately activating more intensive interventions.

The blockchain orchestration layer generated three types of adaptive resilience responses according to the severity of the predicted maritime risk: Dynamic Route Optimization for moderate-risk conditions, Adaptive Supplier Reallocation for elevated-risk conditions, and Emergency Smart Contract Activation for critical-risk conditions. The frequency of these responses is presented in figure 8.

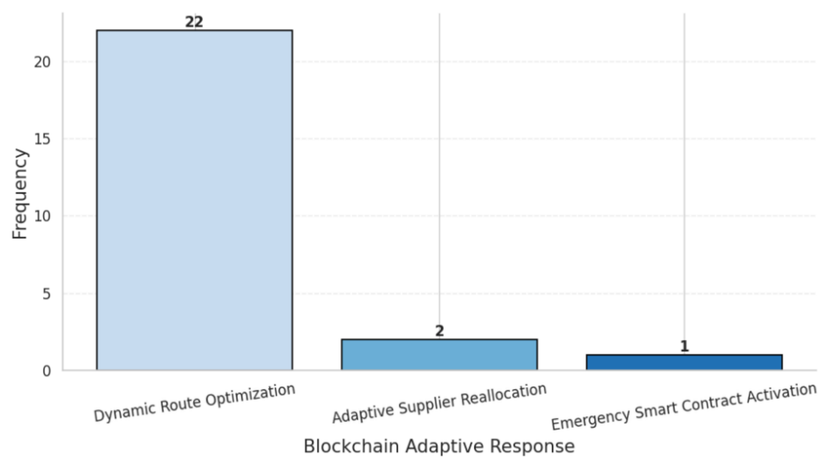

Figure 8 Distribution of Blockchain Adaptive Responses

As illustrated in figure 8, Dynamic Route Optimization was the dominant adaptive response, occurring 22 times, followed by Adaptive Supplier

Reallocation with 2 occurrences and Emergency Smart Contract Activation with 1 occurrence. The predominance of Dynamic Route Optimization indicates that the proposed framework primarily operates as a preventive resilience mechanism, enabling operational adjustments before disruptions escalate to more severe conditions.

The relatively low frequency of Adaptive Supplier Reallocation and Emergency Smart Contract Activation indicates that higher-severity responses were triggered only under a limited number of elevated-risk conditions. This response distribution demonstrates that the proposed blockchain orchestration mechanism provides graduated resilience actions, allowing the intensity of the response to correspond to the predicted level of maritime supply chain risk.

Discussion

The results demonstrate that predictive maritime disruption intelligence can significantly improve adaptive supply chain resilience when integrated with blockchain-based orchestration mechanisms [21], [24]. The proposed framework successfully captured the relationships between congestion indicators, logistics pressure, and freight rate volatility [22], [26].

The correlation analysis showed that supply chain pressure index and congestion-related variables had strong positive relationships with shipping rate fluctuations [23], [25]. This indicates that systemic logistics stress is a major driver of maritime disruption risk. The findings also revealed that delivery reliability decreases significantly during periods of high congestion and operational delays [21], [27].

The XGBoost model achieved strong predictive performance with an R^2 value of 0.842, confirming the effectiveness of the multi-feature prediction framework [24], [26]. Compared with earlier single-variable approaches, the proposed model provided more accurate forecasting by integrating operational, trade, and vulnerability indicators simultaneously [22], [25].

Feature importance analysis identified supply chain pressure index as the dominant predictive factor [21], [23]. This suggests that global maritime disruption is primarily influenced by systemic supply chain instability rather than isolated local congestion events. The adaptive risk analysis further confirmed that disruption risk increased sharply during the COVID-19 logistics crisis between 2020 and 2022 [24], [27].

The blockchain orchestration layer generated adaptive responses such as route optimization, supplier reallocation, and emergency smart contract activation [22], [26]. Most responses were categorized as Dynamic Route Optimization, indicating that the framework mainly supports preventive resilience strategies before disruptions escalate into critical failures [21], [25].

Overall, the findings demonstrate that blockchain-enabled predictive intelligence can improve maritime supply chain resilience through proactive disruption detection and adaptive operational coordination [23], [27].

Conclusion

This study proposed an Adaptive Blockchain-Orchestrated Supply Chain Resilience Framework using predictive maritime disruption intelligence to improve global logistics resilience under disruption conditions. The framework integrated maritime congestion analytics, machine learning prediction, supply chain vulnerability assessment, and blockchain-based adaptive orchestration into a unified resilience system.

The experimental results demonstrated strong predictive performance, with the XGBoost model achieving an R^2 value of 0.842 in forecasting maritime freight volatility. The analysis also revealed that systemic supply chain pressure was the most influential predictor of disruption risk.

The adaptive risk evaluation successfully identified major disruption escalation periods, particularly during the COVID-19 maritime logistics crisis. Furthermore, the blockchain orchestration layer generated dynamic resilience responses capable of supporting proactive mitigation strategies.

In conclusion, the proposed framework demonstrates that predictive blockchain-enabled maritime intelligence can significantly enhance adaptive supply chain resilience through real-time disruption prediction, decentralized coordination, and automated operational response generation.

Declarations

Author Contributions

Conceptualization: R.J.R.; Methodology: R.J.R.; Software: R.J.R.; Validation: R.J.R.; Formal Analysis: R.J.R.; Investigation: R.J.R.; Resources: R.J.R.; Data Curation: R.J.R.; Writing Original Draft Preparation: R.J.R.; Writing Review and Editing: R.J.R.; Visualization: R.J.R.; The author has read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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