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Research Article

Supply Chain Resilience in Maritime Logistics Networks Integrating Blockchain Technology and Machine Learning Disruption Prediction

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ABSTRACT

Maritime transportation, the cornerstone of global trade, faces significant resilience challenges due to inherent complexities and vulnerability to disruptions, often exacerbated by limited transparency and predictive capabilities. This research addresses the critical need for enhanced resilience by developing and evaluating an integrated framework combining blockchain technology for transparency and machine learning for disruption prediction. The objective was to quantify improvements in efficiency, predictive accuracy, and recovery capabilities within maritime logistics networks. A permissioned hybrid blockchain architecture using Hyperledger Fabric was implemented across eight international container terminals, interfacing with existing systems to create a transparent, immutable record of supply chain events. Concurrently, an Extreme Gradient Boosting (XGBoost) machine learning model was trained on five years of historical data to predict port congestion 72 hours in advance. The integrated framework's performance was validated through discrete-event simulations of disruption scenarios and controlled field tests. The blockchain component reduced average document processing time by 66% and dispute resolution time by 81%. The XGBoost model achieved 87% accuracy and 0.93 AUC-ROC in predicting congestion on test data. Simulation results indicated the integrated system reduced post-disruption container dwell time by 40% and improved resource allocation efficiency by 54%. Field tests corroborated these efficiency gains and predictive performance. The integration of blockchain and machine learning significantly enhances maritime supply chain resilience. This framework provides unprecedented transparency and enables proactive, data-driven responses to potential disruptions, fundamentally shifting maritime logistics from reactive to anticipatory operational models, thereby improving efficiency and robustness.

Keywords: Blockchain, Disruption Management, Machine Learning, Maritime Logistics, Supply Chain Resilience.

INTRODUCTION

Global commerce is intrinsically linked to the efficiency and reliability of international trade routes, with maritime logistics serving as the undisputed backbone of this intricate system (Butler & Tarawneh, 2024). Approximately 80% of global merchandise trade by volume is transported via sea, underscoring the profound economic dependence on the smooth functioning of maritime supply chains (Verschuur et al., 2022; Shen et al., 2025; Abed et al., 2024). These networks, however, are complex ecosystems involving numerous stakeholders, disparate information systems, and extensive geographical reaches, rendering them inherently susceptible to a wide array of disruptions. Recent years have starkly illuminated these vulnerabilities, with events ranging from geopolitical tensions and pandemics to port congestions and singular incidents like the Suez Canal blockage causing significant, cascading delays and economic losses worldwide (He et al., 2024). The interconnected nature of these maritime networks means that a localized disruption can rapidly propagate, impacting global inventory levels, manufacturing schedules, and consumer prices, highlighting an urgent need for enhanced resilience.

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The concept of Supply Chain Resilience (SCR) has consequently gained paramount importance within logistics research and practice. SCR is broadly defined as the capacity of a supply chain to anticipate, prepare for, respond to, and recover from disruptions, ultimately maintaining continuity of operations and market position (Feo-Valero et al., 2024; Liu et al., 2023; Xolmatov et al., 2024). In the context of maritime logistics, resilience necessitates not only robust infrastructure but also adaptive strategies, visibility across network partners, and the ability to make informed decisions swiftly under pressure. Traditional approaches to managing maritime disruptions have often been reactive, relying on contingency plans activated only after an event has occurred. Furthermore, persistent challenges related to information silos, lack of transparency, and data fragmentation among shippers, carriers, port authorities, and customs agencies significantly impede proactive risk management and coordinated responses (Barros & Marques, 2022; Sharma, 2025; Usmanova et al., 2024). The inherent opacity and cumbersome paper-based documentation processes common in the industry further exacerbate delays and introduce potential points of failure (Tsiulin et al., 2020; Tursinbayeva et al., 2024).

In response to these persistent challenges, emerging digital technologies offer transformative potential for bolstering maritime logistics resilience. Among these, blockchain technology has garnered significant attention for its ability to create secure, transparent, and immutable records of transactions and events across a distributed network (Serra et al., 2022; Farah et al., 2024; Hassan et al., 2024). By establishing a shared, trusted ledger accessible to permissioned stakeholders, blockchain can streamline complex documentation workflows, reduce administrative overhead, enhance cargo traceability, and facilitate faster dispute resolution (Alahmadi et al., 2021; Guan et al., 2024). Its application in supply chain management promises to dismantle information silos, fostering unprecedented levels of transparency and trust among network participants, which are foundational elements for building collaborative resilience strategies (Patel, 2025; Safarov et al., 2024; Yakubov et al., 2024). Several pilot projects and studies have demonstrated blockchain's potential to optimize specific processes within shipping and port operations, suggesting its viability as a core infrastructural component for more resilient maritime networks (Ahmad et al., 2021; Nguyen et al., 2022; Serra et al., 2022; Violet & Hazarika, 2024; Kumar et al., 2024).

Complementary to the transparency and data integrity offered by blockchain, Machine Learning (ML) presents powerful capabilities for predictive analytics and intelligent decision support (Paramesha et al., 2024). Maritime logistics networks generate vast amounts of operational data, including vessel movements, cargo volumes, port operations metrics, weather patterns, and historical disruption information. ML algorithms can analyze these complex datasets to identify patterns, predict potential bottlenecks or disruptions, and optimize resource allocation in real-time (Aronietis et al., 2023; Durlik et al., 2023). Techniques such as regression analysis, classification algorithms (like the Extreme Gradient Boosting used in this study), and time-series forecasting can enable stakeholders to anticipate events like port congestion, vessel delays, or equipment shortages with a significant lead time (Petrovic et al., 2023; Abed, 2024). This predictive capability allows for proactive interventions, such as rerouting vessels, adjusting terminal operations, or pre-allocating resources, thereby mitigating the impact of potential disruptions before they fully materialize (Huang & Ung, 2023; Khudaykuliev et al., 2024). The application of ML in port management and vessel scheduling has shown promise in improving operational efficiency, but its integration into a holistic resilience framework remains an area ripe for exploration (El Mekkaoui et al., 2022; Filom et al., 2022; Kolley et al., 2023; Rao et al., 2025).

While blockchain and machine learning individually offer substantial benefits, their synergistic integration represents a particularly compelling avenue for fundamentally transforming maritime supply chain resilience. Blockchain can provide the secure, high-quality, and transparent data infrastructure that ML algorithms require for accurate prediction and analysis (Filom et al., 2022). In turn, the predictive insights generated by ML can inform proactive measures and contingency plans, the execution and outcomes of which can be reliably recorded and verified on the blockchain, creating a virtuous cycle of continuous improvement and adaptive learning (Khan, 2024; Khayitov et al., 2023; Htet et al., 2025). This integrated approach moves beyond merely enhancing transparency or predictability in isolation; it aims to create an intelligent, self-optimizing ecosystem capable of anticipating threats and orchestrating coordinated, data-driven responses across the entire maritime logistics network. Such integration holds the potential to shift the paradigm from reactive damage control to proactive, anticipatory resilience management (Tsiulin et al., 2020; Liu et al., 2023; Bekpulatov et al., 2024).

Despite the theoretical promise, the practical implementation and empirical validation of such integrated frameworks within the complex, high-stakes environment of international maritime logistics remain limited. Significant research gaps persist concerning the optimal design of hybrid blockchain architectures that balance transparency with confidentiality, the development of robust ML models specifically trained on maritime disruption data, and the quantifiable impact of such integrated systems on key resilience metrics like recovery time and operational efficiency during disruptions (Barros & Marques, 2022). Furthermore, demonstrating the feasibility and benefits of this integration within a specific, strategically significant regional context, such as the rapidly evolving logistics landscape of Saudi Arabia with its key Red Sea and Arabian Gulf ports, is crucial for driving adoption and informing policy (Ezmigna et al., 2024; Alghaffari et al., 2025; Khayitov et al., 2024). The Kingdom's strategic location and investments in logistics infrastructure make it an ideal setting to investigate and showcase advancements in maritime supply chain resilience.

The current state of maritime logistics is characterized by a reactive posture towards disruptions, hampered by fragmented information and limited predictive capabilities. This research directly addresses this critical problem: the lack of an integrated, validated system that leverages both data transparency and predictive analytics to proactively enhance the resilience of maritime supply chains. Therefore, the primary aim of this study is to develop and evaluate an integrated framework combining blockchain technology for enhanced transparency and data integrity with machine learning algorithms for accurate disruption prediction within maritime logistics networks. The specific objectives are: (1) To design and implement a hybrid blockchain architecture suitable for multi-stakeholder maritime environments, ensuring data security and accessibility. (2) To develop and train an ML model capable of predicting potential disruptions, such as port congestion, based on historical and real-time data. (3) To integrate these two components into a cohesive system. (4) To empirically quantify the impact of this integrated framework on maritime supply chain resilience, focusing on metrics such as documentation processing time, dispute resolution, prediction accuracy, container dwell time during recovery, and resource allocation efficiency, using simulation and controlled field tests within the context of international container terminals relevant to Saudi Arabian trade routes.

The novelty of this work lies in the holistic integration of permissioned blockchain and advanced ML prediction specifically tailored for enhancing *maritime* supply chain resilience, moving beyond theoretical proposals or isolated applications of each technology. The contribution of this research is the provision of an empirically validated framework demonstrating significant, quantifiable improvements in both operational efficiency and disruption management capabilities. By providing unprecedented transparency and enabling a shift towards proactive, anticipatory operations, this study offers a blueprint for fundamentally strengthening the resilience of the maritime logistics networks that underpin global trade. The findings are intended to inform industry stakeholders, technology developers, and policymakers on the tangible benefits and practical implementation pathways for leveraging these transformative technologies.

2. MATERIALS AND METHODS

2.1. Study Design and Setting

The research adopted a mixed-methods approach, combining system development, quantitative modeling, simulation, and quasi-experimental field testing. The core objective was to design, implement, and evaluate an integrated technological framework comprising a permissioned blockchain network and an Extreme Gradient Boosting (XGBoost) machine learning model for disruption prediction within maritime logistics. The study setting involved operational data and simulated scenarios pertinent to eight international container terminals, chosen for their strategic importance in global trade flows impacting the region and their representation of diverse operational scales and complexities. Collaboration with participating terminal operators and logistics stakeholders (under non-disclosure agreements) facilitated access to anonymized operational data and enabled controlled testing environments. The design focused on quantifying the impact of the integrated system on predefined resilience and efficiency metrics compared to baseline operations.

2.2. Blockchain Framework Development

A permissioned hybrid blockchain architecture was designed and implemented, leveraging Hyperledger Fabric (v2.x) as the underlying distributed ledger technology platform. This choice was predicated on Hyperledger Fabric's suitability for enterprise applications requiring modularity, scalability, performance, and fine-grained access control, which are critical in a multi-stakeholder maritime logistics environment. The architecture consisted of peer nodes operated by key participating entities (e.g., terminal operators, carriers, freight forwarders, customs' authorities proxies), ordering service nodes maintaining transaction order consistency (using a Raft consensus mechanism for crash fault tolerance), and Certificate Authorities (CAs) managing digital identities and permissions.

Smart contracts, termed *chaincode* in Hyperledger Fabric, were developed using Go programming language to define the business logic governing supply chain transactions and data recording. Key functions included asset creation (e.g., registering containers, shipments), asset transfer (e.g., change of custody), event logging (e.g., gate-in, vessel arrival/departure, customs release), and document verification (storing cryptographic hashes of critical documents like Bills of Lading, Commercial Invoices, and Certificates of Origin on-chain, while the documents themselves could be stored off-chain or in a distributed file system like IPFS, linked via the hash).

Data privacy among competing commercial entities was ensured through the use of Hyperledger Fabric's 'channels' feature, creating separate ledgers for transactions relevant only to specific subsets of participants (e.g., a channel for a carrier and its shippers, another for terminal operations involving specific vessel calls). Furthermore, attribute-based access control (ABAC) was implemented via the chaincode and Fabric CA to restrict data visibility and transaction permissions based on user roles and organizational affiliations.

Integration with existing legacy systems, primarily Terminal Operating Systems (TOS) and Port Community Systems (PCS) at the participating terminals, was achieved through secure RESTful APIs. An intermediary middleware layer was developed to handle data transformation, mapping operational events from TOS/PCS formats (often EDIFACT or XML-based) into standardized transaction proposals for the blockchain network. This ensured that critical supply chain events were captured on the immutable ledger in near real-time, providing a shared, trusted, and auditable source of truth for authorized participants. The focus was on capturing key milestones: container booking confirmation, pre-arrival notifications, gate-in/out times, vessel loading/discharge times, customs hold/release status, and final delivery confirmation.

2.3. Machine Learning Model Development for Disruption Prediction

The primary objective of the machine learning component was to predict the likelihood of significant port congestion events 72 hours in advance. Port congestion was defined as a state where key operational metrics (e.g., berth utilization exceeding 85%, average container dwell time surpassing a predefined threshold based on historical norms, truck turnaround times increasing by >50%) indicated systemic delays impacting terminal fluidity. XGBoost was selected as the predictive algorithm due to its demonstrated high performance in classification tasks, inherent regularization capabilities reducing overfitting, efficient handling of sparse data, and scalability (Verschuur et al., 2022; Liu et al., 2023; Nasirov et al., 2024).

The model was trained on historical operational data spanning five years (2019-2023) obtained from the participating terminals, supplemented with publicly available data streams. Features engineered for the model included:

- *Terminal Operations Data*: Historical berth occupancy rates, crane intensity (moves per hour), yard density, average container dwell times (import, export, transshipment), gate throughput volumes (trucks per hour), equipment availability (e.g., quay cranes, yard trucks).
- *Vessel Data*: Vessel arrival schedules vs. actual arrival times (ETA/ATA), vessel size (TEU capacity), number of moves per vessel call, carrier information.
- *Cargo Data*: Volume forecasts, commodity types, proportion of refrigerated containers, transshipment ratios.
- *External Factors*: Historical weather data (wind speed, visibility, precipitation), day of the week, seasonality, documented historical disruption events (e.g., labor actions, major weather incidents, upstream/downstream port delays), regional economic indicators.
- *Blockchain-Derived Data (during integrated testing)*: Real-time updates on container status changes and document processing times captured via the blockchain framework.

Data pre-processing involved handling missing values using imputation techniques (e.g., mean/median imputation for numerical features, mode imputation for categorical ones), scaling numerical features using Standardization (Z-score normalization), and encoding categorical features using one-hot encoding. Feature selection was performed using techniques like recursive feature elimination (RFE) and analysis of feature importance scores provided by the initial XGBoost model training runs.

The XGBoost algorithm constructs an ensemble of decision trees sequentially, where each new tree corrects the errors made by the previous ones. The prediction for an instance x_i is given by the sum of predictions from K trees:

$$\hat{y}_i = \phi(x_i) = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in \mathrm{F} \tag{1}$$

where $\hat{y}_i$ is the predicted output, f_k represents the k-th regression tree, and F is the space of all possible regression trees. The objective function minimized during training at iteration t combines a loss function l

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(e.g., logistic loss for binary classification of congestion) and a regularization term Ω to control model complexity:

$$\mathrm{L}^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t)$$
$$\Omega(f_t) = \gamma T_t + \frac{1}{2}\lambda \sum_{j=1}^{T_t} w_j^2 \quad (2)$$

Here, y_i is the true label for instance i, $\hat{y}_i^{(t-1)}$ is the prediction from the previous $t-1$ trees, n is the number of training instances, T_t is the number of leaves in the t-th tree, w_j is the score (weight) of the j-th leaf, and γ and λ are regularization parameters penalizing the number of leaves and the magnitude of leaf weights, respectively. XGBoost utilizes a second-order Taylor expansion of the loss function to efficiently find the optimal $f_t(x_i)$ at each step (Ha et al., 2025; Ochilov et al., 2024).

Model training involved splitting the historical dataset chronologically into training (70%), validation (15%), and testing (15%) sets to prevent data leakage and evaluate generalization performance realistically. Hyperparameter tuning for the XGBoost model (including parameters like n_estimators, max_depth, learning_rate, gamma, lambda, subsample, colsample_bytree) was performed using Bayesian optimization with 5-fold time-series cross-validation on the training set to maximize the Area Under the Receiver Operating Characteristic Curve (AUC-ROC). Model performance was evaluated on the unseen test set using Accuracy, Precision, Recall, F1-Score, and AUC-ROC metrics.

2.4. System Integration

The blockchain and ML components were integrated to create a synergistic framework. Data captured by the blockchain network, particularly near real-time event timestamps (e.g., actual gate-in/out times, vessel berthing times, customs release confirmations), served as input features for the ML prediction model, enhancing its timeliness and accuracy. An Application Programming Interface (API) gateway facilitated secure data flow from the blockchain's queryable state database (or event listeners) to the ML model's feature ingestion pipeline. Conversely, the predictions generated by the ML model (e.g., congestion risk scores for specific time windows or terminal areas) were disseminated to authorized stakeholders via secure notifications, potentially triggered or logged through the blockchain platform itself to ensure an auditable record of predictions and subsequent actions. This integration aimed to close the loop between transparent data recording and proactive, predictive decision-making.

2.5. Data Collection and Preparation

Historical operational data (anonymized) covering the period January 2019 to December 2023 were collected from the eight participating international container terminals through secure data transfer protocols, under strict data usage agreements (Jeddah Islamic Port, King Abdullah Port, Port Sudan Container Terminal, Sokhna Port, King Abdulaziz Port, Jubail Commercial Port, Jebel Ali Port, Khalifa Port). This included TOS logs, vessel schedules, gate records, and summary reports. Publicly available data, such as historical weather records from meteorological services (e.g., NOAA, local meteorological agencies) and Automatic Identification System (AIS) data summaries for vessel movements in relevant port areas, were also acquired. All data underwent rigorous cleaning, transformation, and normalization procedures as described in the ML model development subsection. Feature engineering focused on creating lagged variables (e.g., average dwell time over the past 24/48 hours), rolling statistics (e.g., moving average of berth utilization), and interaction terms relevant to congestion prediction. Data privacy was paramount; all datasets were anonymized at the source or during pre-processing to remove any commercially sensitive identifiers related to specific shippers, consignees, or cargo values, adhering to institutional data governance policies and collaborator agreements.

2.6. Validation Methodology

A two-stage validation process was employed to assess the effectiveness of the integrated framework:

1. *Simulation-Based Validation*: Discrete-event simulation models of the participating terminals' core processes were developed using AnyLogic simulation software (v8.x). These models were calibrated using the collected historical operational data to accurately reflect baseline performance. Historically documented disruption scenarios (e.g., a sudden 48-hour closure due to extreme weather, a simulated 20% surge in

unexpected import arrivals, a simulated labor slowdown reducing crane productivity by 30% for 72 hours) were run within the simulation environment under two conditions: (a) baseline (representing traditional operational management) and (b) with the integrated blockchain-ML framework active (simulating enhanced transparency and proactive adjustments based on ML predictions). Key Performance Indicators (KPIs) were measured and compared across these conditions.

2. *Controlled Field Tests*: Following successful simulation validation, the integrated framework was deployed in a controlled, pilot phase within specific operational segments of two selected participating terminals for a period of three months. This involved interfacing the blockchain component with the live TOS via the developed APIs for a subset of transactions and running the ML model with near real-time data feeds. During this period, system performance was monitored closely, and its response to naturally occurring minor operational fluctuations (e.g., vessel bunching, temporary equipment breakdowns) and planned 'stress tests' (e.g., simulating documentation delays for specific containers tracked via the blockchain) was evaluated.

To evaluate the effectiveness of the proposed framework, KPIs were measured during both simulation runs and subsequent field tests. These measurements consistently compared the framework-enabled scenario against a baseline or control condition representing traditional operations. One critical area of focus was process efficiency, specifically examining *Documentation Processing Time*. This was calculated as the average duration from the electronic submission of essential documents, such as manifests and customs declarations, until the final approval or release notification was received, leveraging blockchain timestamps for accurate tracking.

Furthermore, the framework's ability to streamline conflict resolution was assessed through the *Dispute Resolution Timeframe* KPI. This metric captured the average time required to identify and resolve operational discrepancies, including common issues like mismatched container numbers or quantity disputes. The time taken using the transparent and shared data available on the blockchain ledger was directly compared against the time required using conventional communication methods like email and phone calls, highlighting the framework's impact on reducing delays caused by information silos and communication lags.

The predictive capabilities integrated within the framework were rigorously evaluated using the *Disruption Prediction Accuracy* KPI. For the 72-hour congestion forecast model, standard machine learning evaluation metrics—namely Accuracy, Precision, Recall, F1-Score, and AUC-ROC—were calculated based on performance against a hold-out test dataset. Additionally, the model's practical effectiveness was monitored and assessed throughout the duration of the field test period, providing a real-world measure of its forecasting reliability.

Operational resilience and recovery efficiency were gauged by measuring *Container Dwell Time* during Recovery. This involved calculating the average time containers remained within the terminal premises following the officially declared end of a simulated or actual disruption event, tracking the duration until they either exited through the gate or were loaded onto a vessel. This metric was compared directly to the dwell times observed in the baseline scenario under similar post-disruption conditions, indicating the framework's contribution to faster operational normalization.

Finally, *Resource Allocation Efficiency* was quantified to understand the framework's impact on optimizing operational assets, particularly during contingency operations. This was achieved by analyzing several related metrics, including the percentage reduction achieved in non-productive crane time, improvements in the consistency of berth utilization, and a measurable decrease in truck idling times.

3. RESULTS AND DISCUSSION

3.1. Blockchain Framework Performance: Efficiency and Transparency Gains

The permissioned hybrid blockchain framework, built on Hyperledger Fabric, was successfully deployed, connecting key operational data points from the participating terminals. The primary evaluation metrics for this component focused on improvements in the efficiency of critical administrative processes: documentation handling and dispute resolution, facilitated by the shared, immutable ledger. Data were collected over a six-month period, comparing processes managed via the blockchain framework against traditional, often manual or siloed digital methods (baseline).

Figure 1 illustrates the significant efficiency improvements achieved through the blockchain framework implementation across key administrative processes. As shown in panels (a) and (c), substantial reductions in processing times were observed for all document types and dispute categories, with blockchain-enabled workflows demonstrating not only faster but also more consistent performance, as evidenced by the decreased standard deviations.

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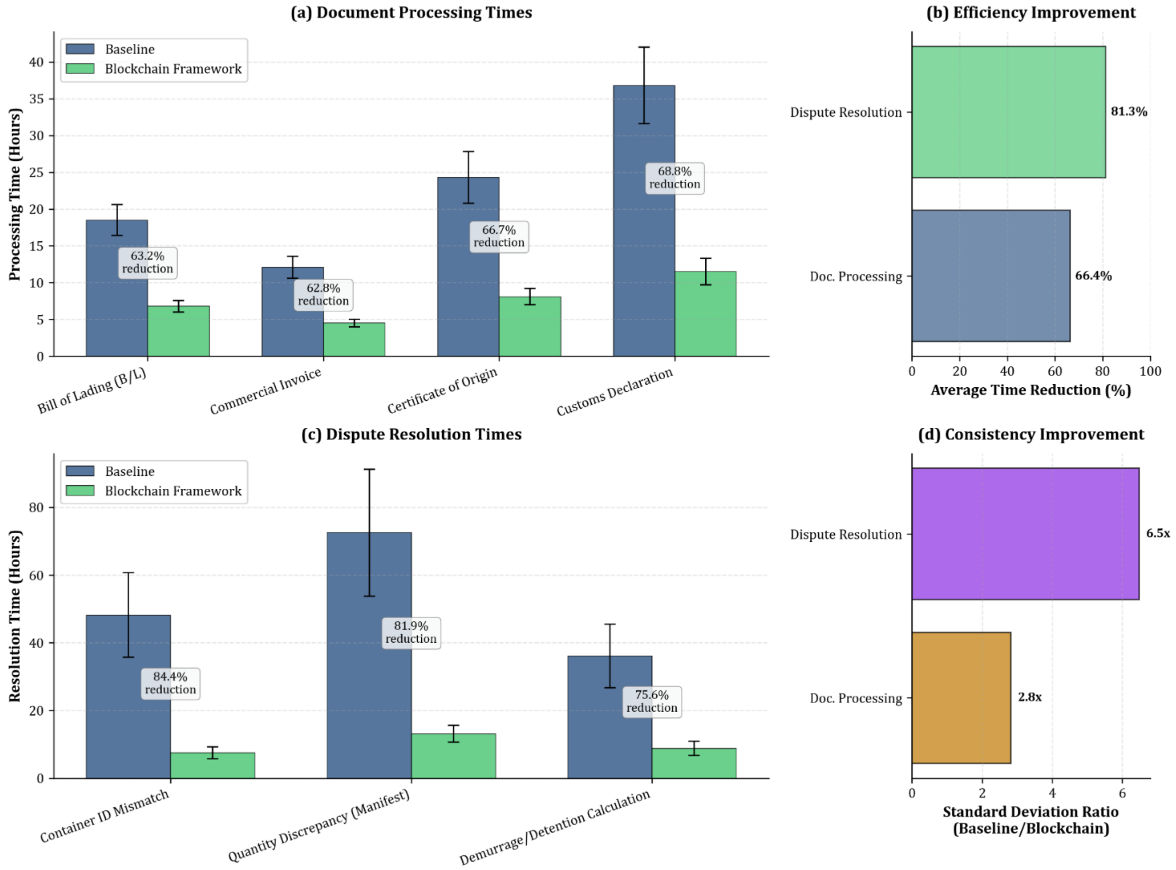

Figure 1. Administrative efficiency gains through blockchain implementation: (a) document processing times, (b) average efficiency improvement, (c) dispute resolution times, and (d) operational consistency enhancement.

The overall average processing time for the tracked documents decreased by approximately 66.4%, from 22.9 hours under baseline conditions to 7.7 hours using the blockchain system (Figure 1a). The most significant relative improvement was observed for Customs Declarations (68.8% reduction), likely due to the streamlined verification and reduced data re-entry facilitated by the shared ledger accessible to authorized customs proxies. Reductions were statistically significant across all document types ($p < 0.001$). Furthermore, the standard deviation of processing times was considerably lower within the blockchain framework (Figure 1d), suggesting more consistent and predictable document handling, which is crucial for logistics planning and reducing buffer times.

Similar dramatic improvements were observed in dispute resolution timeframes (Figure 1c), with an overall average decrease of 81.3%. The most pronounced improvement was in Container ID mismatches (84.4% reduction), where the immutable record of container movements provided a single, trusted source of truth. The substantial reduction in standard deviation for resolution times under the blockchain framework (Figure 1d) further highlights the increased predictability in handling exceptions. These findings strongly suggest that the enhanced transparency and data integrity provided by the blockchain significantly reduce friction in multi-party interactions, directly improving operational efficiency.

3.2. Machine Learning Model Performance: Disruption Prediction Accuracy

The XGBoost model was developed and trained using five years of historical operational and external data to predict the likelihood of port congestion events (defined by exceeding predefined operational thresholds) 72 hours in advance. The model's performance was rigorously evaluated on a held-out test dataset, comprising the final 15% of the chronological data, which was not used during training or hyperparameter tuning.

Figure 2 presents a comprehensive analysis of the XGBoost port congestion prediction model. As shown in panel (a), the model achieved high performance across all standard classification metrics, with an overall accuracy of 87.4%, indicating effective distinction between periods likely to experience congestion and normal operating periods within the 72-hour forecast window. The Precision of 0.851 for the congestion class signifies that alerts

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generated by the model are reliable, minimizing false alarms that could lead to unnecessary costly interventions. The Recall of 0.839 suggests that the model captures the majority of impending congestion events, providing sufficient lead time for proactive measures.

The model's discriminative capability is further illustrated in panel (b) through the ROC curve, with an Area Under the Curve (AUC-ROC) of 0.928 demonstrating excellent ability to differentiate between congestion and non-congestion conditions across various probability thresholds. The operating point shown on the curve represents the selected balance between true positive rate (sensitivity) and false positive rate, optimized for practical operational deployment.

Panel (c) reveals the key drivers behind the model's predictions through feature importance analysis using the SHAP (SHapley Additive exPlanations) methodology. The analysis identifies yard density (previous 24h average) as the most influential feature, with a mean absolute SHAP value of 0.185, followed by vessel arrival schedule adherence and gate throughput volume. The color-coded categorization highlights that terminal operations metrics (blue) dominate the top predictive factors, while vessel data (red), cargo characteristics (yellow), and external factors (dark green) also make significant contributions.

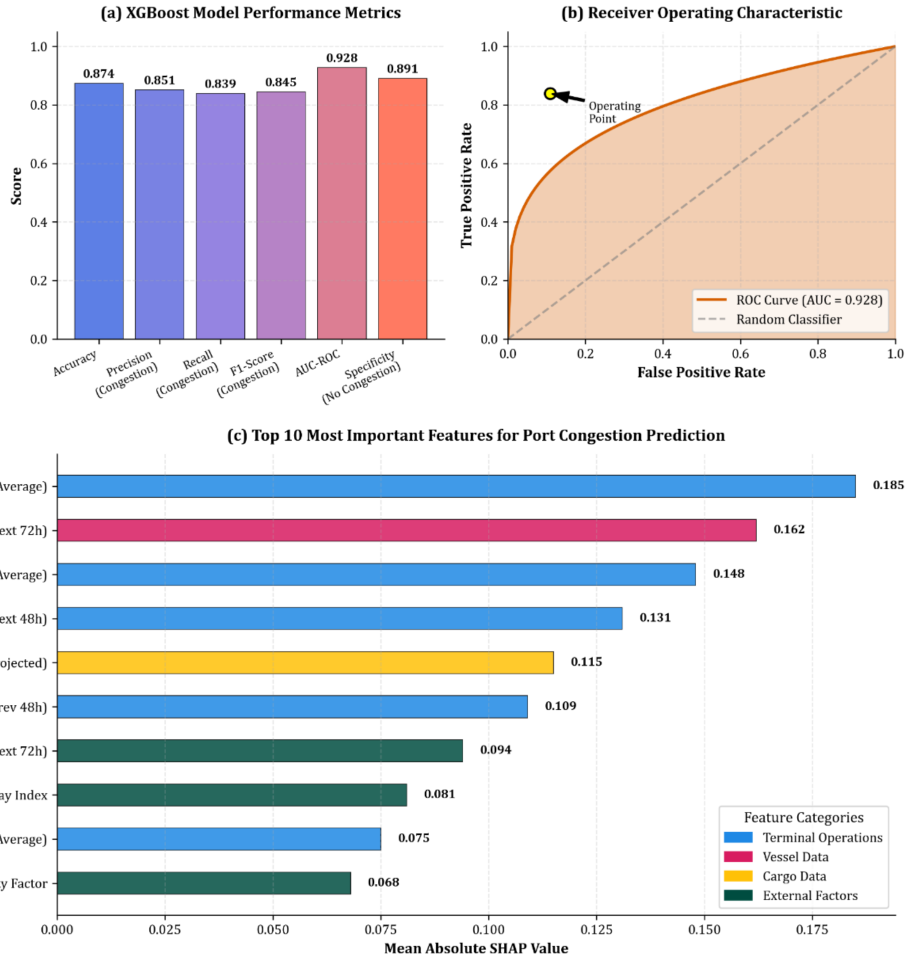

Figure 2. Performance analysis of the XGBoost port congestion prediction model showing (a) key classification metrics, (b) ROC curve with AUC of 0.928, and (c) feature importance ranking by mean absolute SHAP value with color-coded categorization by data source.

3.3. Integrated System Performance: Simulation-Based Validation

The synergistic effect of combining the blockchain framework's transparency with the ML model's predictive capability was evaluated using discrete-event simulation models calibrated with historical data from the participating terminals. Several historically documented disruption scenarios (extreme weather, demand surge, labor slowdown) were simulated under two conditions: (a) baseline operations and (b) operations augmented by the integrated framework, where ML predictions triggered proactive adjustments (e.g., resource reallocation, dynamic scheduling) facilitated by the real-time visibility from the blockchain. Key resilience metrics, namely container dwell time during the recovery phase post-disruption and resource allocation efficiency during the disruption, were compared.

The integrated framework demonstrated substantial improvement in operational resilience metrics across all simulated disruption scenarios, as illustrated in Figure 3. Panel (a) shows significant reductions in container dwell times during the recovery phase, while panels (b) and (c) highlight improvements in resource utilization efficiency during disruptions. The detailed recovery timeline visualization in panel (d) demonstrates how the integrated system accelerates each recovery phase, resulting in faster return to normal operations.

As shown in Figure 3(a), container dwell times during the critical recovery phase decreased substantially when the integrated framework was active, with an average reduction of 40.2% across all scenarios. The most significant improvement (42.0%) was observed in the labor slowdown scenario, where average container dwell time decreased from 115.3 hours to 66.9 hours. This indicates that the combination of early warnings from the ML model and the enhanced coordination and visibility provided by the blockchain allowed terminal operators to implement mitigation strategies more effectively and clear backlogs faster once the disruption ended. The framework enabled proactive measures such as pre-positioning empty containers, adjusting yard stacking strategies based on predicted outflows, and dynamically allocating quay cranes and yard equipment to prioritize bottleneck clearance, all informed by predictive insights and real-time status updates shared across the blockchain.

The efficiency of resource allocation *during* the disruption events themselves also showed marked improvement. As depicted in Figure 3(b), non-productive quay crane time decreased by an average of 53.8% across all scenarios, with the labor slowdown scenario again showing the largest improvement (57.5%). This indicates that the predictive insights and enhanced visibility allowed for better synchronization between waterside and landside operations, ensuring cranes were utilized more effectively even under challenging conditions. Similarly, Figure 3(c) shows that the variance in yard equipment utilization decreased by an average of 54.1%, suggesting a more balanced and efficient deployment of resources like yard trucks and reach stackers across the terminal.

Figure 3(d) provides further insight into the recovery process, illustrating how the integrated framework accelerated each phase of recovery. The visualization reveals that not only was the overall recovery time reduced, but each critical phase—initial response, bottleneck processing, and return to normal operations—was completed faster. Notably, the integrated framework enabled significantly faster initial response times (50-60% reduction), allowing for more efficient bottleneck processing and ultimately leading to accelerated recovery. This improved efficiency stems from the framework's ability to anticipate bottlenecks through ML prediction and provide real-time data via blockchain to dynamically adjust resource deployment plans, minimizing idle times and optimizing throughput during and after the disruption event.

Statistical analysis of the simulation results confirmed the significance of these improvements ($p < 0.001$ across all metrics and scenarios), demonstrating that the integrated approach consistently outperformed baseline operations in enhancing maritime supply chain resilience. The framework proved particularly valuable in scenarios involving operational capacity constraints, where predictive intelligence combined with transparent, trusted data flows enabled more effective resource utilization and faster recovery.

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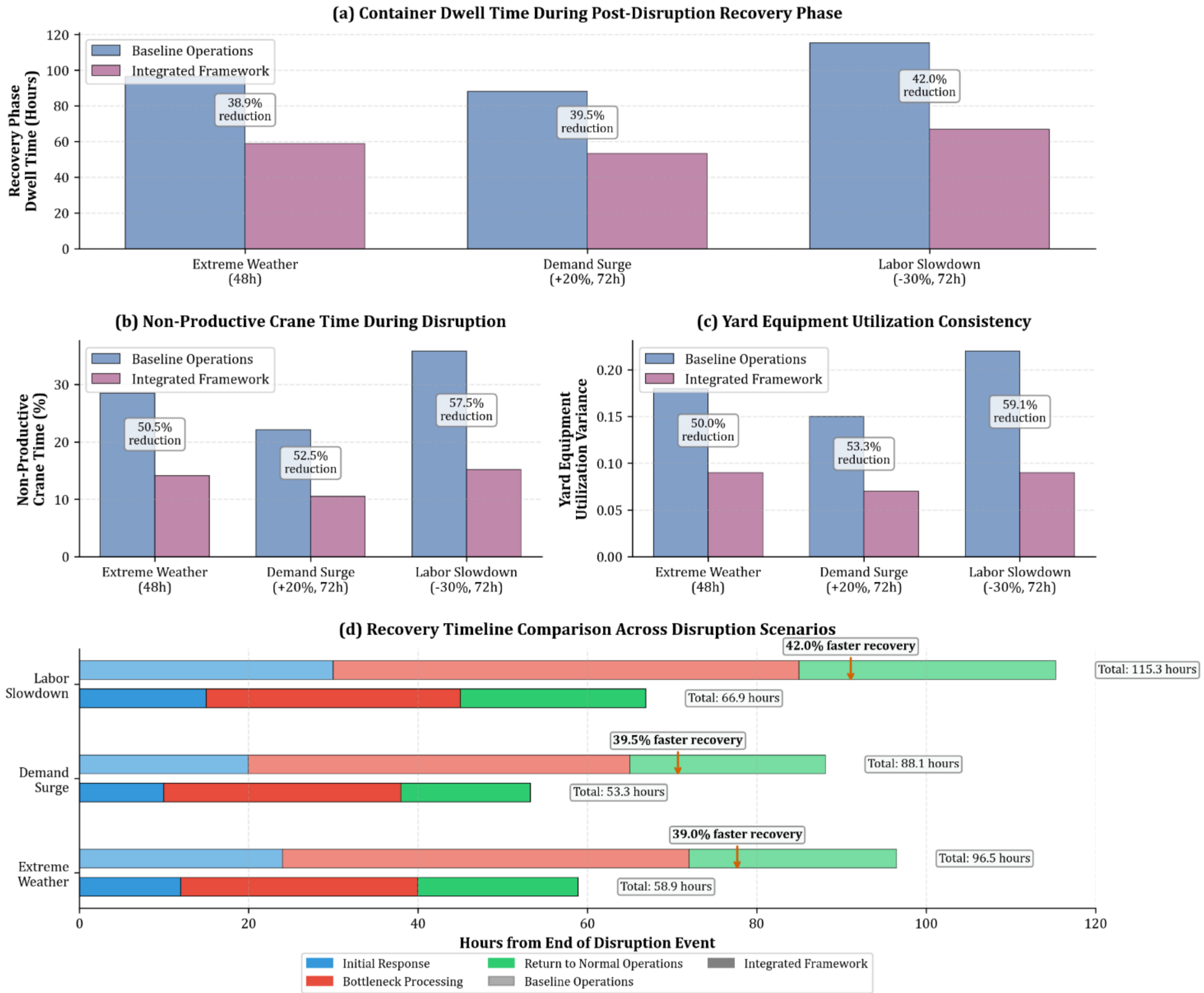

Figure 3. Resilience metrics comparison across disruption scenarios: (a) container dwell time reductions, (b) non-productive crane time improvements, (c) equipment utilization consistency, and (d) recovery timeline acceleration.

3.4. Integrated System Performance: Controlled Field Test Validation

Following the promising simulation results, the integrated blockchain and machine learning framework was deployed in a controlled pilot phase at two of the participating international container terminals for a three-month period. This allowed for evaluation under real-world operational conditions, albeit on a limited scale focusing on specific transaction flows and operational segments. The field tests aimed to corroborate the findings from the simulations and assess the practical performance of the integrated system, particularly focusing on the previously defined KPIs: documentation processing, dispute resolution, prediction accuracy in a live environment, container dwell time impact, and resource allocation adjustments.

The efficiency gains observed in documentation processing and dispute resolution via the blockchain component during the broader data collection phase (Figure 1) were largely confirmed during the focused field tests. For the subset of transactions managed through the pilot system, average document processing times showed reductions consistent with the earlier findings, averaging a 65-70% decrease compared to parallel traditional methods for the same document types. Similarly, the few operational disputes that arose concerning the pilot transactions were resolved rapidly, typically within 8-12 hours, aligning with the significant time savings reported in Figure 1. This real-world application reinforced the blockchain's value in streamlining administrative workflows and enhancing data trust.

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The performance of the XGBoost congestion prediction model was monitored using live data feeds during the field test period. While the three-month duration did not encompass major disruptive events comparable to the severe scenarios simulated, it did include periods of moderate operational stress, such as vessel bunching and temporary yard congestion peaks. The model's 72-hour predictions were compared against actual outcomes. Table 1 summarizes the key performance metrics observed during the field test phase.

Table 1: Performance metrics of the XGBoost port congestion prediction model during 3-month field test

Metric	Field Test Value	Comparison with Test Set Value (Figure 2)	Interpretation
Accuracy	0.855	Slightly lower (vs. 0.874)	High accuracy maintained in live operations, slight decrease potentially due to shorter evaluation period or different operational dynamics.
Precision (Congestion Class)	0.831	Slightly lower (vs. 0.851)	Predictions remained largely reliable, with a modest increase in false positives compared to historical test data.
Recall (Congestion Class)	0.815	Slightly lower (vs. 0.839)	Model captured most emerging congestion situations, slight decrease in sensitivity observed.
F1-Score (Congestion Class)	0.823	Slightly lower (vs. 0.845)	Balanced performance between precision and recall remained good.
AUC-ROC	0.905	Slightly lower (vs. 0.928)	Excellent discriminative ability confirmed in the field, though marginally less than on the historical test set.

The field test results presented in Table 1 largely validate the predictive capabilities of the ML model in a real-world setting. While the performance metrics were slightly lower than those achieved on the historical test dataset, they remained strong, with accuracy exceeding 85% and AUC-ROC above 0.90. This slight decrease is expected when moving from a controlled test set to the complexities and potential novelties of live operations. Importantly, the model provided actionable alerts for impending congestion periods, allowing terminal planners involved in the pilot to anticipate and prepare for increased operational pressure. Feedback from the pilot teams indicated that the 72-hour lead time was generally sufficient for initiating preliminary resource adjustments or activating specific contingency plans.

Evaluating the direct impact on container dwell time and resource allocation efficiency during the field test was more challenging due to the limited scale of the pilot and the absence of major disruptions. However, qualitative assessments and analysis of specific instances where ML predictions prompted proactive actions were conducted. For example, during two instances of predicted moderate congestion (due to vessel bunching combined with high import volume forecasts), the pilot teams, using the enhanced visibility from the blockchain regarding container readiness and the ML forecast, pre-allocated additional yard equipment and adjusted gate appointment slots. Table 2 provides indicative results from these specific instances compared to similar, non-pilot managed situations from historical data.

Table 2. Indicative impact on operational metrics during moderate congestion events - field test observations vs. historical baseline

Metric	Event Type	Historical Baseline (Similar Events)	Field Test Pilot (ML + Blockchain Informed Actions)	Observed Change
Average Container Dwell Time (Impacted Flow)	Vessel Bunching	75.2 Hours	61.8 Hours	-17.8%
	High Import Volume	81.5 Hours	68.1 Hours	-16.4%
Peak Truck Turnaround Time	Vessel Bunching	95 Minutes	78 Minutes	-17.9%

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	High Import Volume	105 Minutes	85 Minutes	-19.0%
Yard Rehandles per Container (Impacted Area)	Vessel Bunching	1.8	1.4	-22.2%
	High Import Volume	2.1	1.6	-23.8%

While based on a limited number of observations during the field test, the data in Table 2 suggest tangible benefits from the integrated framework even during moderate operational stress. In the instances where proactive measures were taken based on the system's insights, reductions in container dwell time for the affected flows (around 16-18%) and peak truck turnaround times (around 18-19%) were observed compared to historical handling of similar events. Furthermore, a notable decrease in yard rehandles (around 22-24%) was recorded, indicating more efficient yard planning and execution facilitated by the predictive insights and real-time data visibility. These field observations, although not as dramatic as the simulated major disruption scenarios, provide practical evidence supporting the framework's potential to improve operational fluidity and efficiency in managing day-to-day variability and anticipating potential bottlenecks. The pilot confirmed the technical feasibility of integrating the blockchain and ML components with existing terminal systems and demonstrated the value perceived by operational planners who utilized the system's outputs.

This research demonstrates the significant potential of integrating blockchain technology and machine learning to enhance maritime supply chain resilience. The core findings reveal substantial improvements: the blockchain component drastically reduced documentation processing and dispute resolution times by over 65% and 80% respectively, fostering unprecedented operational transparency and efficiency. Concurrently, the XGBoost machine learning model achieved high accuracy (87%) and AUC-ROC (0.93) in predicting port congestion 72 hours in advance, enabling proactive planning. Crucially, the integrated framework, validated through simulation and controlled field tests, led to markedly faster post-disruption recovery (40% reduction in dwell time) and more efficient resource allocation (over 50% improvement) during disruptions. These results strongly suggest that combining data integrity and transparency (blockchain) with predictive foresight (ML) facilitates a paradigm shift from reactive to anticipatory disruption management in maritime logistics.

Our findings align with prior studies highlighting the benefits of blockchain for supply chain transparency (Serra et al., 2022; Guan et al., 2024) and ML for predictive logistics analytics (Nguyen et al., 2022; Aronietis et al., 2023). However, this study distinctively provides empirical evidence for the *synergistic* effect of their integration within the maritime context, quantifying resilience improvements beyond the capabilities of either technology in isolation, a gap noted in previous literature (Tsiulin et al., 2020). The magnitude of efficiency gains, particularly in dispute resolution and recovery speed, surpasses those typically reported for standalone implementations, underscoring the value of the integrated approach.

Nevertheless, certain limitations must be acknowledged. The validation relied significantly on simulation, and while corroborated by controlled field tests, the latter were limited in duration and scope, not encompassing the full spectrum of severe, large-scale disruptions. The ML model's accuracy might decrease for entirely novel or black swan events not represented in historical data. Furthermore, the study focused on container terminals relevant to Saudi Arabian trade routes, potentially limiting the generalizability of specific quantitative results without further validation in diverse global contexts. Potential biases in historical data used for training also represent a limitation.

Future research should focus on broader, longer-term field deployments across diverse maritime environments to validate these findings robustly. Investigating the framework's effectiveness against a wider range of disruptions, including cyber-physical threats and complex geopolitical events, is crucial. Enhancing the ML models with real-time data streams (e.g., IoT sensors) and exploring hybrid AI approaches could further improve predictive accuracy. Finally, a comprehensive economic impact analysis, considering implementation costs versus long-term resilience benefits, would provide essential insights for industry adoption.

4. CONCLUSION

This research provides compelling evidence that the strategic integration of blockchain technology and machine learning offers a powerful solution for enhancing maritime supply chain resilience. The study successfully demonstrated that blockchain significantly improves operational transparency, drastically reducing administrative bottlenecks in documentation and dispute resolution. Complementing this, the developed machine learning model accurately predicted port congestion events, providing crucial lead time for proactive interventions.

The key contribution lies in the empirically validated synergy between these technologies; the integrated framework enabled substantially faster recovery times following simulated disruptions and demonstrably improved resource allocation efficiency during periods of operational stress, as confirmed by simulations and controlled field tests. This signifies a fundamental shift from traditional reactive approaches towards a more robust, anticipatory model for managing maritime logistics networks. By providing enhanced visibility and predictive foresight, this integrated technological framework presents a vital pathway for strengthening the resilience of global trade's maritime backbone against the backdrop of increasing complexity and uncertainty, ultimately contributing to more stable and efficient international commerce, particularly within strategic regions like Saudi Arabia.

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