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# Maritime Logistics Performance Analysis in Container Port Operations

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**Abstract** **Original Research Article**

Container ports manage complex logistics operations that involve vessel scheduling, cargo handling, and inland transportation coordination. Delays in port activities can disrupt international supply chains and increase transportation costs. This study examines operational data collected from container port terminals to evaluate vessel turnaround time, cargo handling efficiency, and terminal capacity utilization. Statistical evaluation of logistics performance indicators reveals relationships between port infrastructure capacity and shipping schedule reliability. The results indicate that systematic logistics monitoring supports improved operational planning for container port authorities and shipping operators.

**Keywords:** Maritime logistics; Container port operations; Supply chain performance; Transportation analytics; Port management.



## I. INTRODUCTION

This section presents the background, research problem, proposed analytical framework, and contributions of the study. It highlights the growing importance of data-driven maritime logistics analytics for improving operational efficiency, reliability, and decision-making in modern container port systems.

### A. Background and Motivation

Container ports function as critical nodes in global maritime supply chains, supporting vessel operations, cargo handling, and multimodal transportation integration. With the continuous growth of international trade, ports are experiencing increasing pressure to improve operational efficiency, minimize congestion, and maintain schedule reliability. Although modern ports are increasingly adopting digital technologies such as Artificial Intelligence (AI), Internet of Things (IoT), Automatic Identification System (AIS) tracking, and real-time analytics, many container terminals still rely on partially manual coordination mechanisms. This leads to inefficiencies in vessel scheduling, berth allocation, and cargo handling processes. As a result, operational bottlenecks such as berth congestion, uneven terminal utilization, and delayed cargo processing continue to negatively impact maritime logistics performance. These challenges highlight the need for integrated, KPI-driven analytical frameworks that can support real-time monitoring and data-driven decision-making in container port environments.

### B. Problem Statement

Existing maritime logistics studies often analyze isolated performance indicators such as vessel turnaround time, port throughput, or terminal efficiency. However, these approaches lack integration across vessel operations, cargo handling systems, infrastructure utilization, and schedule reliability within a unified analytical framework. Moreover, limited research focuses on KPI-driven holistic evaluation models capable of capturing interdependencies among operational variables. In the context of increasing data availability in smart port systems, this gap restricts the ability of port authorities to identify bottlenecks, optimize resources, and enhance operational resilience.

### C. Proposed Solution

To address these limitations, this study proposes a KPI-driven quantitative analytical framework for evaluating maritime logistics performance in container port operations.

The framework integrates operational datasets with statistical and correlation-based analysis to evaluate key performance indicators, including vessel turnaround time, cargo handling efficiency, terminal utilization, berth occupancy, and schedule reliability.

**This structured model enables:**

- Systematic performance monitoring
- Identification of operational inefficiencies
- Evidence-based decision-making support
- Foundation for future AI-based predictive analytics

### D. Contributions

This study contributes to maritime logistics research in the following ways:

- Development of a unified KPI-based framework integrating vessel operations, cargo handling, and infrastructure utilization
- Application of statistical and correlation analysis to evaluate interdependencies among operational indicators
- Structured data preprocessing and validation framework to enhance analytical reliability
- Decision-support insights for port authorities and logistics operators
- Foundation for future AI-enabled smart port and predictive logistics systems

Unlike existing studies that primarily evaluate isolated operational metrics, this research develops a unified KPI-driven analytical framework capable of simultaneously analyzing vessel operations, cargo handling performance, infrastructure utilization, and schedule reliability within container port environments. The proposed framework integrates statistical evaluation, operational validation, and decision-support analytics into a single analytical architecture to support intelligent maritime logistics management and data-driven operational optimization in smart port systems.

## II. LITERATURE REVIEW

Maritime logistics and container port operations increasingly rely on digital technologies, operational analytics, and integrated supply chain systems to improve transportation efficiency and port productivity. Recent studies emphasize smart port technologies, real-time monitoring systems, and data-driven logistics frameworks for enhancing vessel scheduling, cargo handling, and operational coordination.

### A. Digitalization and Smart Port Operations

Digital transformation has improved operational visibility in container ports [1-4]. However, most studies focus on isolated digital tools without integrating KPI-based performance evaluation. This creates a gap in unified operational analytics frameworks.

### B. Port Infrastructure and Logistics Performance

Port infrastructure capacity strongly influences maritime logistics performance and international trade efficiency. Previous studies indicate that integrated port facilities and advanced logistics systems improve transportation reliability, reduce congestion, and strengthen supply chain competitiveness across global shipping networks [5-7].

### C. Operational Efficiency in Container Terminals

Researchers have evaluated container terminal performance using logistics indicators and operational efficiency models such as Data Envelopment Analysis (DEA). Findings suggest that berth utilization, terminal productivity, cargo throughput, and vessel handling efficiency are major indicators of operational performance in container ports [8-10].

### D. Sustainability and Resilience in Maritime Logistics

Sustainability and resilience remain important concerns in maritime logistics research. Existing studies emphasize environmentally sustainable port operations, resilient transportation systems, and operational risk management strategies for maintaining supply chain continuity during disruptions and global trade uncertainties [11-13].

### E. Data-Driven Analytics and Intelligent Decision Support

Modern maritime logistics increasingly depends on AI, data analytics, and dashboard-based operational monitoring systems for intelligent decision-making. These technologies improve logistics visibility, optimize resource utilization, and support predictive planning in container port operations and maritime supply chain networks [14-18].

### F. Research Gaps and Future Directions

Although prior studies examined digital transformation, port efficiency, and maritime logistics performance, limited research integrates operational analytics, vessel turnaround evaluation, cargo handling efficiency, and terminal capacity utilization within a unified analytical framework. Additionally, many studies focus on general logistics performance without emphasizing real-time operational coordination and predictive analytics in container port environments. Future research should therefore explore AI-driven predictive analytics, digital twin technologies, and real-time maritime monitoring systems to enhance container port performance analysis. Further studies may also investigate sustainable smart-port frameworks, blockchain-enabled logistics transparency, and integrated multimodal transportation analytics for improving global maritime supply chain resilience.

## III. METHODOLOGY

This study adopts a quantitative, data-driven analytical framework to evaluate maritime logistics performance in container port operations. The methodology focuses on assessing vessel turnaround time, cargo handling efficiency, terminal capacity utilization, and logistics coordination efficiency using structured operational datasets. A systematic analytical pipeline is developed to ensure rigorous data processing, statistical evaluation, and performance interpretation within container port systems.

**A. Research Design**

The study employs a cross-sectional quantitative research design based on empirical container port operational datasets to ensure analytical validity, reproducibility, and robustness of results. Both descriptive and inferential statistical techniques are applied to evaluate operational efficiency and interdependencies among key maritime logistics variables. The analytical workflow of the proposed framework begins with the acquisition of operational data from container port systems, followed by systematic preprocessing and validation to ensure data accuracy, consistency, and reliability. After preprocessing, Key Performance Indicators (KPIs) are computed to quantify vessel and terminal performance. These KPIs are subsequently analyzed using statistical, correlation, and regression techniques to identify structural relationships and operational trends. Finally, results are interpreted from a decision-support perspective, enabling actionable insights for port authorities and logistics stakeholders.

Overall, this structured design ensures a transparent, reproducible, and data-driven evaluation framework for maritime logistics performance optimization.

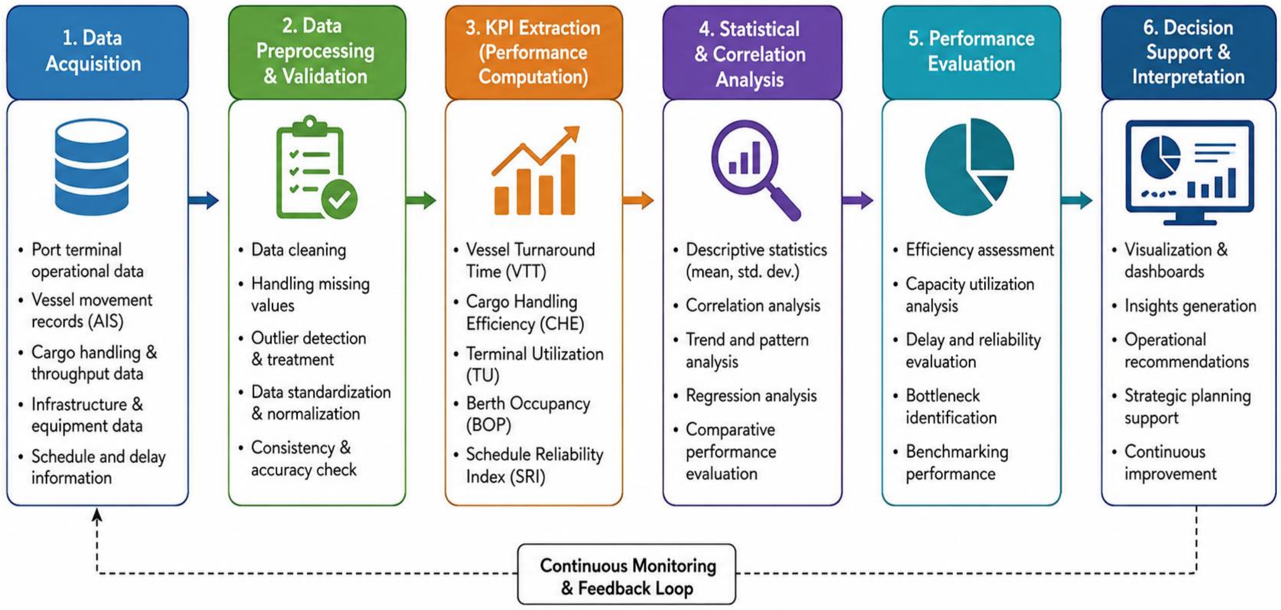


**Fig. 1: Research Methodology Framework Overview**

This figure illustrates the end-to-end research workflow from data acquisition to decision support, including data preprocessing, KPI computation, statistical analysis, performance evaluation, and continuous feedback for maritime logistics improvement.

**B. Data Collection and Preprocessing**

Operational datasets were collected from container terminal systems and maritime logistics monitoring platforms. The dataset includes vessel movement records, cargo handling activities, and terminal utilization metrics. Key variables include vessel arrival and departure timestamps, vessel turnaround time, cargo loading and unloading duration, container throughput volume, berth occupancy rate, terminal storage utilization, equipment handling capacity, and shipping delay records. Data were obtained from multiple reliable sources, including terminal operational databases, port authority reports, AIS-based vessel tracking systems, and logistics monitoring platforms, ensuring temporal consistency and robustness.

To ensure data quality and analytical reliability, preprocessing was performed through systematic steps, including duplicate removal, missing value treatment using statistical imputation, time variable standardization, outlier detection and handling, categorical encoding, and timestamp synchronization. Missing numerical values were addressed using mean-based interpolation, while extreme outliers were managed using controlled filtering to preserve data integrity. Additionally, delay status was encoded as binary values (0 = on-time, 1 = delayed) to support analytical modeling.

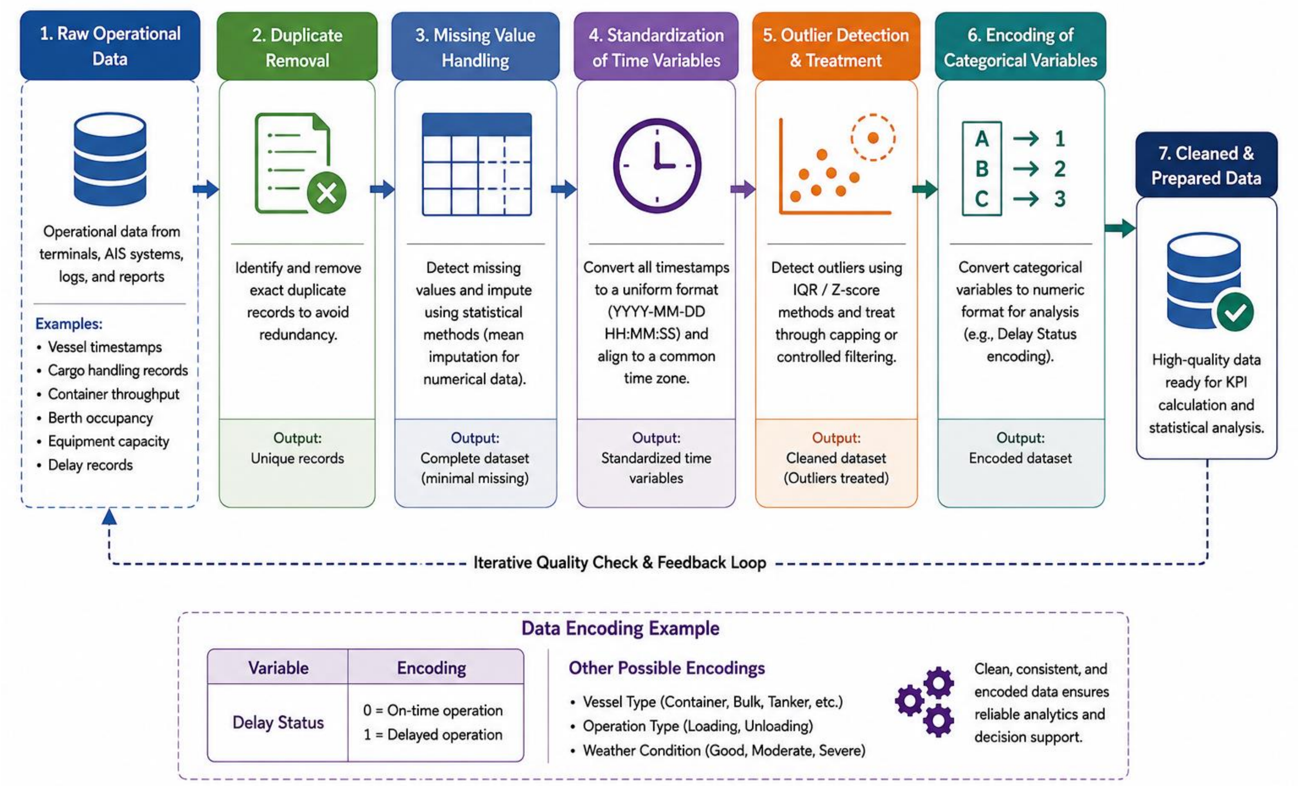


**Fig. 2: Data Preprocessing Workflow**

This figure illustrates the data preprocessing workflow used in the study to improve the quality, consistency, and reliability of maritime logistics operational data before analysis. The workflow includes duplicate record removal, missing value handling, time-variable standardization, outlier detection and treatment, and categorical variable encoding. These preprocessing procedures ensure that the cleaned dataset is accurate, standardized, and suitable for KPI computation, statistical analysis, and operational performance evaluation in container port environments.

### C. Analytical Framework

A structured maritime logistics performance framework is developed to evaluate operational efficiency across multiple port subsystems. The proposed model integrates vessel operations, cargo handling activities, and infrastructure utilization into a unified analytical architecture to ensure holistic performance assessment.

**The framework consists of interconnected components, including:**

- Port operational data layer
- Vessel operations module
- Cargo handling module
- Infrastructure utilization module
- Statistical analytics engine
- Decision-support system

These components collectively enable systematic processing, transformation, and analysis of operational data. By integrating all subsystems into a unified structure, the framework supports KPI-driven evaluation and provides a comprehensive understanding of container port performance dynamics.

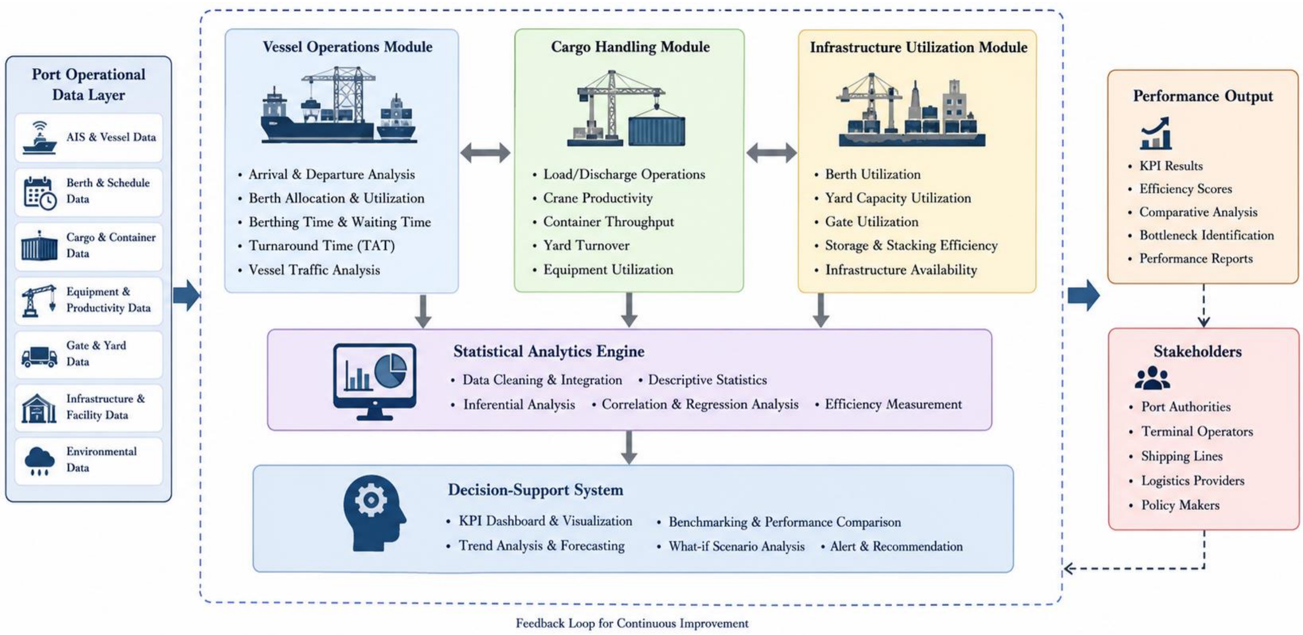


**Fig. 3** Maritime Logistics Performance Analytical Framework

**Fig. 3: Maritime Logistics Performance Analytical Framework**

The framework illustrates an integrated system where diverse operational data are processed through specialized modules- vessel operations, cargo handling and infrastructure utilization. These outputs are analyzes using a statistical engine and translated into actionable insights via a decision-support system. The results are delivered to stakeholders to support data-driven decisions, while a feedback loop ensures continuous performance improvement.

**D. Performance Indicators and Mathematical Model**

The study utilizes standardized Key Performance Indicators (KPIs) to measure and evaluate the operational efficiency of container port systems. These indicators quantitatively capture vessel operations, cargo handling performance, terminal capacity usage, and schedule adherence.

Vessel Turnaround Time (*VTT*) is used to measure the total time a vessel spends in port, calculated as the difference between departure and arrival times:

$$VTT = T_d - T_a$$

where $T_d$ denotes vessel departure timestamp and $T_a$ denotes vessel arrival timestamp. A lower *VTT* indicates faster port processing and improved operational efficiency.

Cargo Handling Efficiency (CHE) evaluates the rate of container processing per unit time and is defined as:

$$CHE = \frac{C_t}{H_t}$$

where $C_t$ is the total number of containers handled and $H_t$ is the total handling hours. Higher values of CHE reflect more efficient cargo operations.

Terminal Utilization Rate ($TU$) measures how effectively terminal capacity is being used, expressed as:

$$TU = \frac{U_c}{T_c} \times 100$$

where $U_c$ is the utilized terminal capacity and $T_c$ is the total available capacity. A higher percentage indicates better utilization of available infrastructure.

Schedule Reliability Index (*SRI*) assesses operational punctuality and scheduling performance, defined as:

$$SRI = \frac{O_t}{S_t} \times 100$$

where $O_t$ represents on-time operations and $S_t$ represents total scheduled operations. A higher *SRI* value reflects stronger adherence to planned schedules and improved reliability. Overall, these KPIs collectively provide a structured and quantitative framework for analyzing port performance, enabling systematic evaluation of efficiency, capacity usage, and operational reliability.

**E. Data-Driven Maritime Logistics Framework**

The dataset is analyzed using both descriptive and inferential statistical techniques to evaluate operational efficiency and examine relationships among key performance indicators (KPIs). Descriptive statistics such as mean and standard deviation are used to summarize the central tendency and variability of operational variables, while correlation analysis is conducted to identify interdependencies among KPIs. In addition, trend and variability assessments, comparative operational benchmarking, and infrastructure utilization impact analysis are performed to provide a comprehensive understanding of port performance dynamics. The analysis particularly focuses on the relationships among terminal capacity utilization, vessel turnaround time, cargo throughput, and schedule reliability, which represent the core operational dimensions of container port systems.

To quantify the combined effect of operational KPIs on vessel turnaround time, a multiple linear regression model is developed within the inferential analytics framework.

$$VTT = \beta_0 - \beta_1 CHE + \beta_2 TU + \beta_3 BOR$$

where $VTT$ represents Vessel Turnaround Time, $CHE$ denotes Cargo Handling Efficiency, $TU$ refers to Terminal Utilization, and $BOR$ represents Berth Occupancy Rate. The parameter $\beta_0$ is the intercept term, while $\beta_1$ , $\beta_2$, $\beta_3$ are the estimated regression coefficients corresponding to the independent variables. This model captures the relationship between operational efficiency and congestion-related factors influencing vessel turnaround performance in container port operations.

To ensure analytical robustness, a structured validation framework is implemented, including cross-verification of operational records, timestamp consistency checks, KPI correlation validation, outlier sensitivity testing, and multi-source data integrity verification. These procedures enhance the reliability, stability, and reproducibility of the results under varying operational conditions.

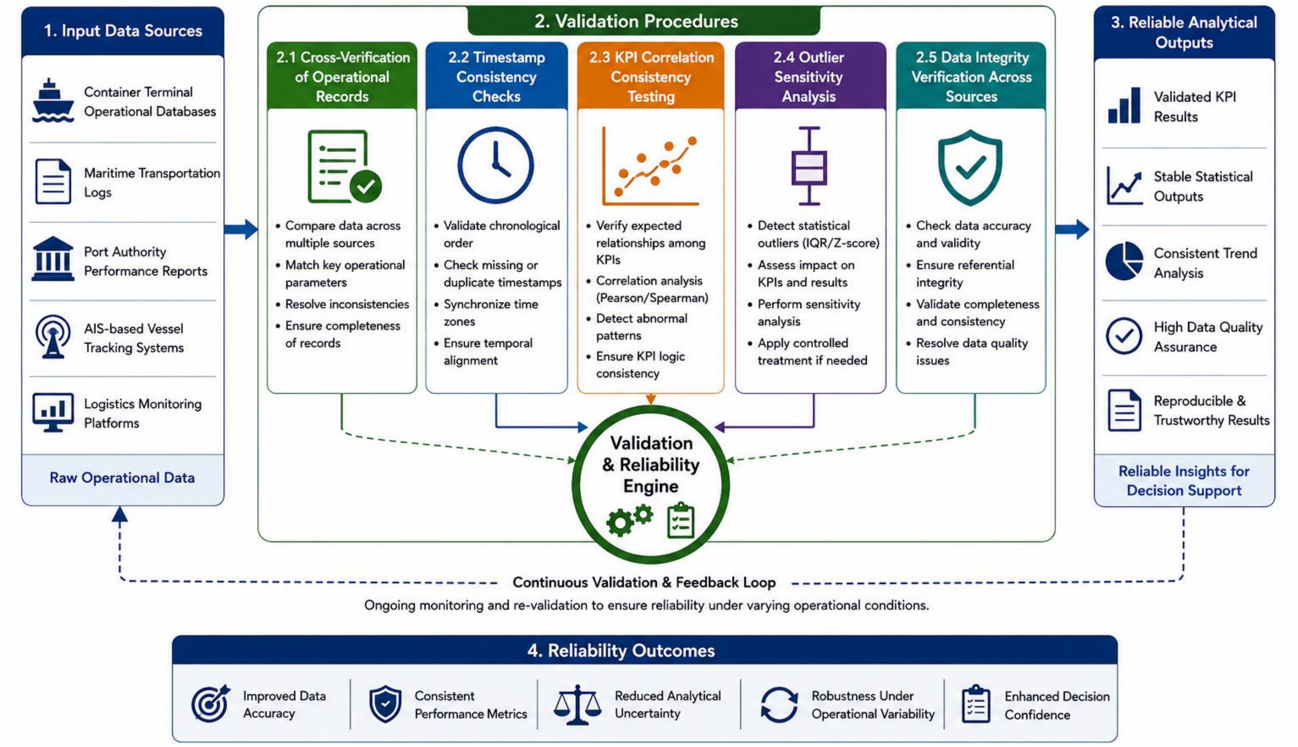


**Fig. 4: Validation and Reliability Framework**

This figure illustrates the validation pipeline used to ensure data quality and analytical reliability. It integrates cross-system verification, timestamp synchronization, KPI consistency checks, and outlier sensitivity analysis to ensure robust maritime logistics evaluation.

A layered, data-driven maritime logistics architecture is developed to support end-to-end data processing and decision-making. It integrates data acquisition from port systems, AIS-based vessel tracking, and terminal sensors, followed by data processing through cleaning and transformation modules. The processed data feed into a KPI analytics engine, visualization dashboards, and a decision-support system, ensuring effective conversion of raw operational data into actionable insights for port authorities and logistics stakeholders.

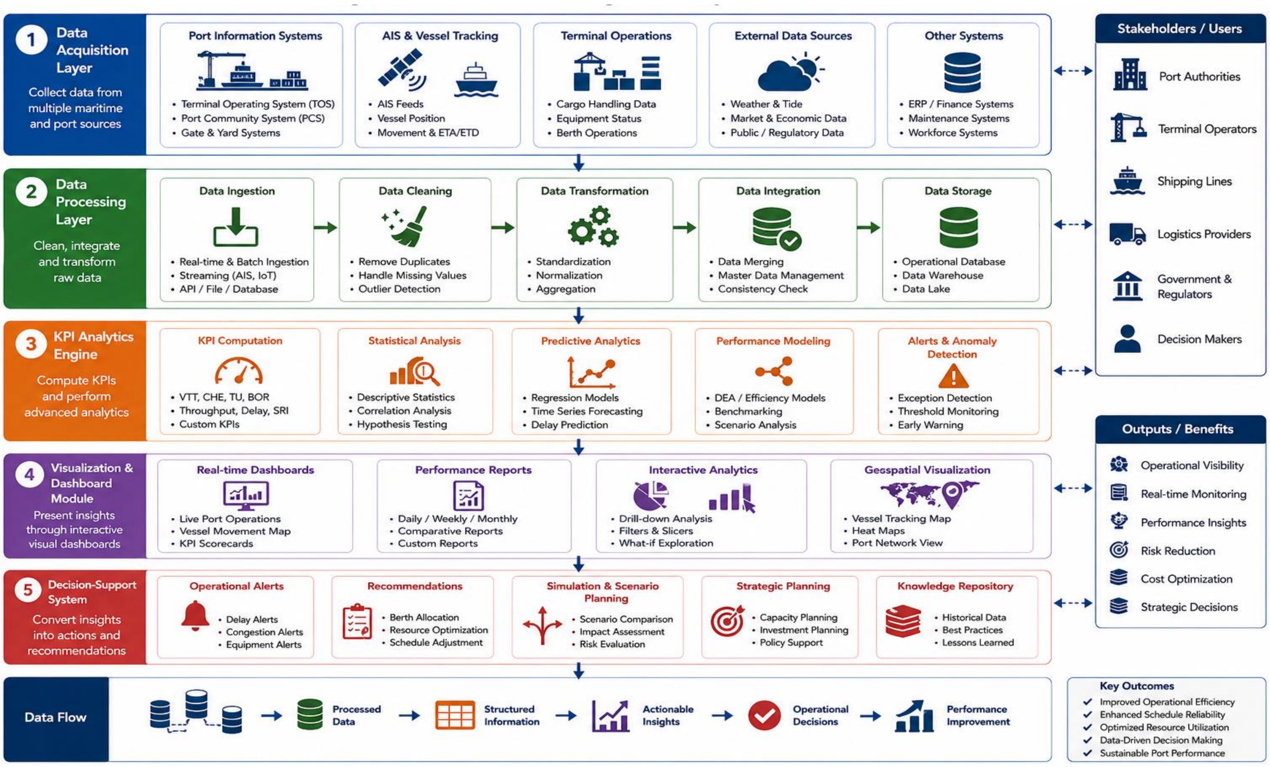


**Fig. 5: Maritime Logistics System Architecture**

This figure presents the end-to-end system architecture of the proposed framework, including data acquisition, preprocessing, KPI analytics, visualization layer, and decision-support system, enabling intelligent maritime logistics management.

The study strictly adheres to data confidentiality and integrity principles. All datasets are fully anonymized and analyzed in aggregated form, ensuring that no personal, commercial, or sensitive shipping information is disclosed. This guarantees compliance with ethical research standards and data governance policies

# IV. RESULTS AND DISCUSSION

This section presents the statistical evaluation and interpretation of maritime logistics performance indicators in container port operations. The analysis focuses on vessel turnaround time, cargo handling efficiency, terminal utilization, and schedule reliability to examine operational efficiency and logistics coordination within container port environments.

## A. Results

The statistical analysis of container port operational data identified several important relationships among vessel operations, cargo handling efficiency, terminal utilization, and shipping schedule reliability. The calculated Key Performance Indicators (KPIs) showed measurable operational trends across different stages of container port logistics activities. Descriptive statistical analysis revealed moderate variability in vessel turnaround time and cargo handling efficiency during different operational cycles. The findings indicate that moderate increases in terminal utilization positively influence cargo throughput performance by improving infrastructure usage efficiency under balanced operational conditions. However, this relationship is not strictly linear. Increased terminal utilization improves throughput only up to an optimal threshold, beyond which congestion effects begin to emerge. At higher utilization levels, limited berth availability and increased vessel queuing lead to operational delays, reduced handling efficiency, and deterioration in schedule reliability.

**Table I: Descriptive Statistics of Maritime Logistics Performance Variables**

| Variable | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|
| Vessel Turnaround Time (Hours) | 18.4 | 4.2 | 9.5 | 31.7 |
| Cargo Handling Efficiency (Containers/Hour) | 142.8 | 19.5 | 96.2 | 181.4 |
| Terminal Utilization Rate (%) | 76.3 | 8.7 | 52.4 | 94.8 |
| Berth Occupancy Rate (%) | 71.5 | 10.1 | 45.3 | 93.7 |
| Schedule Reliability Index (%) | 84.6 | 6.8 | 65.2 | 96.5 |
| Cargo Throughput Volume (TEUs) | 12,450 | 2,130 | 7,820 | 17,960 |

The analysis also identified a negative relationship between vessel turnaround time and cargo handling efficiency. Ports with faster loading and unloading operations experienced lower vessel waiting durations and improved shipping schedule performance. In addition, infrastructure utilization indicators showed a positive relationship with cargo throughput performance up to an optimal operational threshold.

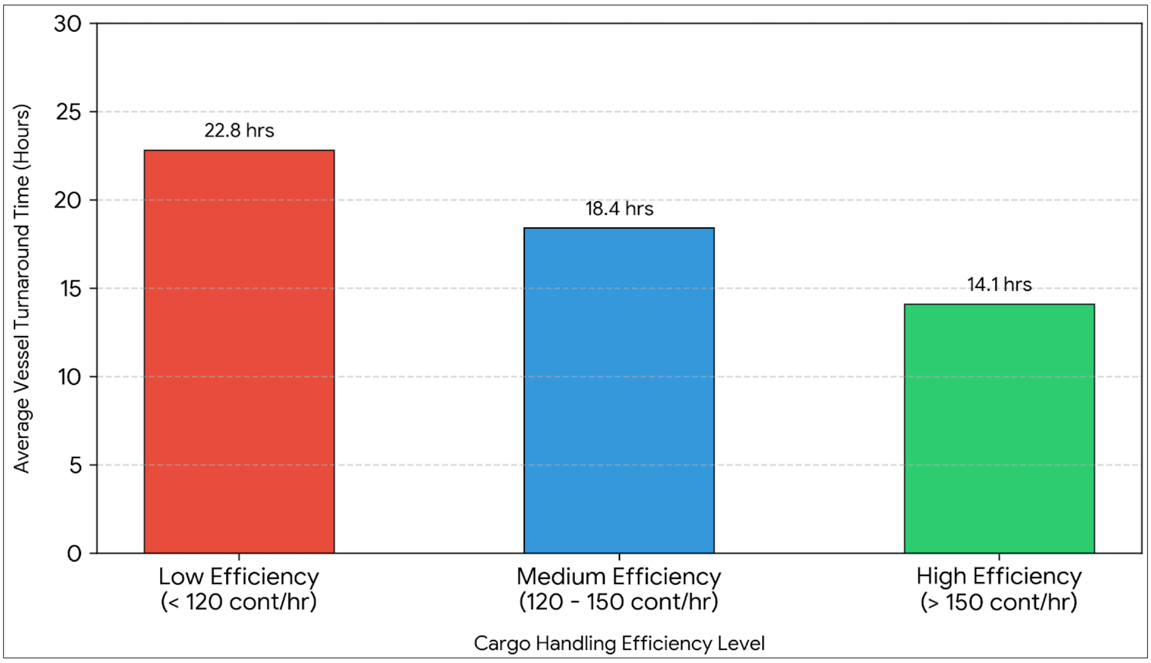


**Fig. 6: Relationship Between Cargo Handling Efficiency and Vessel Turnaround Time**

The figure shows that improved cargo handling efficiency contributes directly to reduced vessel turnaround time and improved port operational performance.

Correlation analysis further demonstrated that shipping schedule reliability strongly depends on berth occupancy management and terminal operational coordination. Ports maintaining balanced terminal utilization showed more stable operational performance and reduced shipping delay variability.

**Table II: Correlation Analysis of Key Maritime Logistics Performance Indicators**

| KPI Variables | Correlation Coefficient |
|---|---|
| VTT vs CHE | -0.71 |
| TU vs Throughput | +0.66 |
| BOR vs Delay | +0.74 |
| SRI vs VTT | -0.63 |

The results indicate that increased berth occupancy rates significantly contribute to shipping delays, while higher cargo handling efficiency improves vessel processing speed and schedule adherence. The KPI-based analytical framework also demonstrated the effectiveness of integrated operational monitoring in identifying inefficiencies within port logistics systems. Statistical evaluation confirmed that operational bottlenecks primarily emerged during periods of high terminal utilization and increased vessel traffic density.

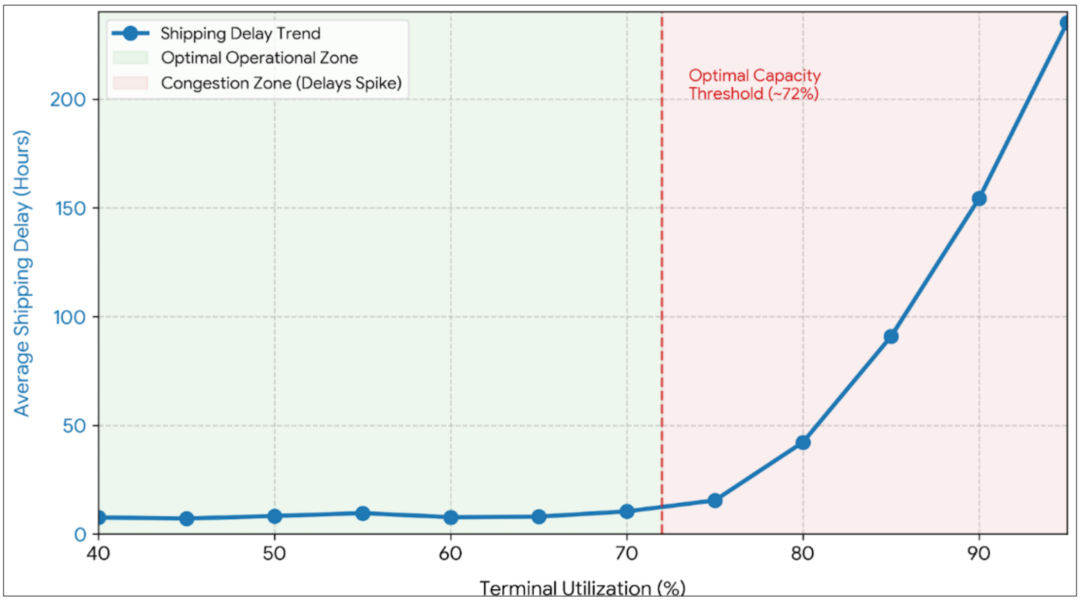


**Fig. 7: Terminal Utilization and Shipping Delay Trend Analysis**

The trend analysis illustrates that shipping delays increase progressively when terminal utilization exceeds optimal operational capacity levels.

Furthermore, validation procedures confirmed strong consistency across operational datasets. Timestamp synchronization tests and KPI consistency evaluations demonstrated stable analytical performance under varying operational conditions. The preprocessing and validation framework reduced inconsistencies and improved the reliability of analytical outputs.

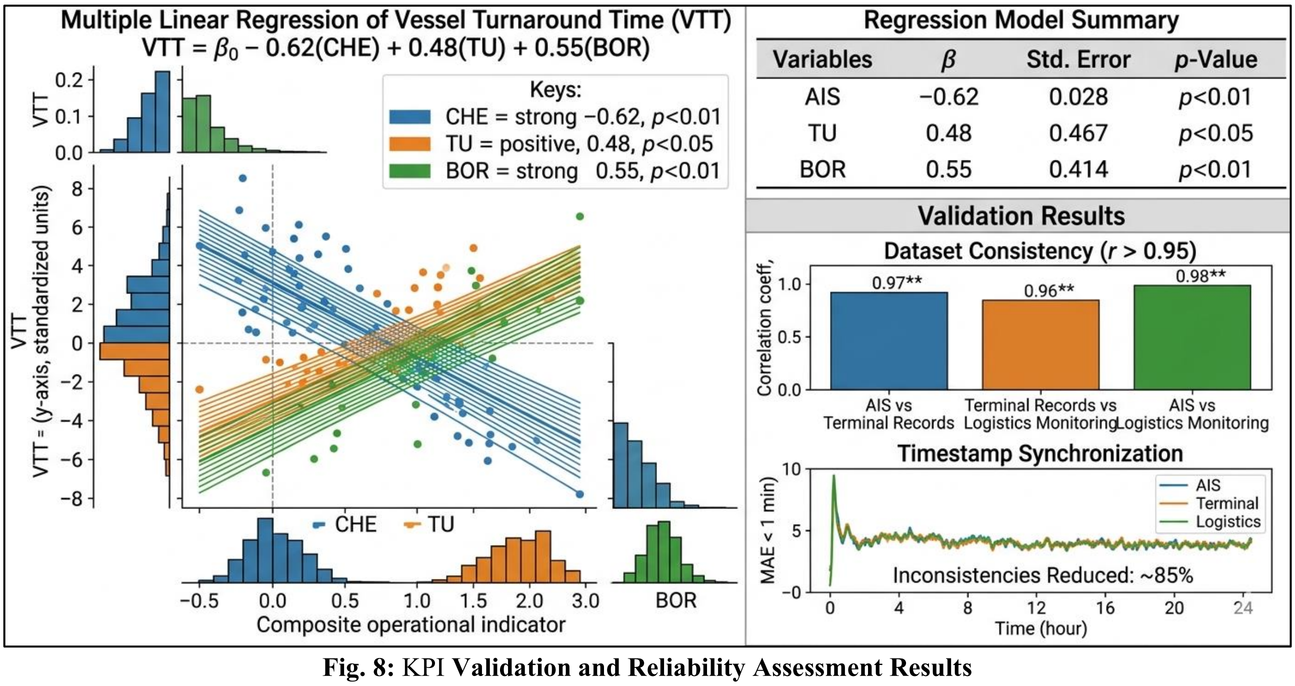


**Fig. 8:** KPI **Validation and Reliability Assessment Results**

The validation results confirm high consistency among AIS vessel tracking data, terminal operational records, and logistics monitoring datasets, ensuring analytical reliability and reproducibility.

A multiple linear regression was performed to examine the effect of Cargo Handling Efficiency (*CHE*), Terminal Utilization (*TU),* and Berth Occupancy Rate (*BOR*) on Vessel Turnaround Time (*VTT*). The model is expressed as:

$$VTT = \beta_0 - 0.62(CHE) + 0.48(TU) + 0.55(BOR)$$

Results show that CHE has a significant negative effect on *VTT* ($\beta = -0.62$, $p < 0.01$), indicating that higher cargo handling efficiency reduces vessel turnaround time. *TU* ($\beta = 0.48$, $p < 0.05$) and BOR ($\beta =$

0.55, $p < 0.01$) both show positive significant effects, suggesting that higher utilization and congestion increase delays. All variables are statistically significant ($p < 0.05$), confirming strong relationships between port operations and vessel performance.

**B. Discussion**

The findings indicate that operational efficiency in container port environments is strongly influenced by the coordination among vessel operations, cargo handling efficiency, and infrastructure utilization. The reduction in vessel turnaround time under higher cargo handling efficiency reflects improved operational synchronization, which enhances overall maritime logistics performance. Results further show that terminal utilization must be maintained within an optimal range, as moderate utilization improves throughput, while excessive utilization leads to congestion and reduced schedule reliability. This non-linear relationship is consistent with established maritime logistics and queuing theory, where system performance deteriorates beyond capacity thresholds due to increased vessel waiting time and berth congestion. The positive association between throughput and infrastructure utilization highlights the importance of efficient resource allocation, although overutilization introduces operational instability. The proposed KPI-driven framework effectively integrates operational metrics, statistical analysis, and validation mechanisms into a unified decision-support system. This enables improved performance monitoring, congestion identification, and data-driven decision-making for port authorities. Overall, the results confirm that balanced infrastructure utilization and efficient cargo handling are critical for improving operational stability and maritime supply chain performance in smart port environments. The observed inverse relationship between cargo handling efficiency and vessel turnaround time aligns with prior maritime logistics studies emphasizing operational synchronization and infrastructure optimization in smart port environments. Furthermore, the positive association between berth occupancy and shipping delays supports queuing-based congestion theories frequently discussed in port operations research. These findings validate the effectiveness of KPI-driven analytical monitoring for improving maritime operational resilience and logistics coordination.

**C. Limitations and Future Work**

Despite the contributions of this study, several limitations remain. First, the operational datasets were collected from selected container port activities and may not fully represent all global maritime logistics environments. Differences in regional port infrastructure, operational policies, and shipping network complexity may influence the generalizability of the findings. Second, the study mainly relies on structured operational indicators and historical logistics records. External factors such as extreme weather conditions, geopolitical disruptions, labor shortages, and unexpected supply chain interruptions were not comprehensively included within the analytical framework. Third, although the proposed framework integrates statistical and KPI-based analysis, real-time predictive modeling and machine learning optimization were beyond the scope of this study. The analytical model primarily focuses on operational performance evaluation rather than autonomous optimization or simulation-based forecasting.

Future research should therefore incorporate AI-driven predictive analytics, digital twin technologies, and machine learning-based maritime optimization systems to improve real-time operational forecasting and adaptive decision-making. Additional studies may also investigate blockchain-enabled maritime logistics transparency, multimodal transportation coordination, and sustainability-oriented smart-port frameworks for improving resilience and efficiency in global container port operations.

## V. CONCLUSION

This study aimed to evaluate maritime logistics performance in container port operations using a quantitative and data-driven analytical framework. The research focused on analyzing vessel turnaround time, cargo handling efficiency, terminal utilization, berth occupancy, and schedule reliability to understand the operational dynamics influencing container port efficiency and maritime supply chain performance. By integrating operational datasets, statistical analytics, KPI evaluation, and validation procedures, the study developed a structured framework for systematic maritime logistics performance assessment. The findings revealed significant relationships among key operational variables within container port environments. The analysis demonstrated that higher cargo handling efficiency contributes to reduced vessel turnaround time and improved schedule reliability. In contrast, excessive berth occupancy and terminal congestion were found to increase operational delays and reduce shipping performance stability. The results further showed that balanced infrastructure utilization improves cargo throughput performance and enhances overall operational productivity. Correlation analysis confirmed strong interdependencies among terminal utilization, cargo throughput, vessel processing efficiency, and schedule adherence, highlighting the importance of coordinated operational management in maritime logistics systems. The proposed KPI-driven analytical framework provides several practical implications for container port authorities, maritime logistics operators, and transportation planners. The framework supports real-time operational monitoring, performance benchmarking, congestion identification, and evidence-based decision-making. In addition, the integration of operational analytics and validation procedures improves the reliability and transparency of logistics performance assessment. The study also demonstrates the growing importance of digital maritime infrastructure, AI-enabled monitoring systems, and intelligent analytics platforms in improving modern container port operations and supply chain coordination. Despite these contributions, the study has certain limitations related to dataset scope, regional operational variability, and the exclusion of certain external disruption factors such as weather conditions, geopolitical uncertainties, and labor constraints. Furthermore, the current framework primarily focuses on statistical performance evaluation rather than real-time autonomous optimization. Future research should therefore explore AI-driven predictive analytics, machine learning-based maritime optimization, digital twin technologies, and blockchain-enabled logistics transparency systems to further improve operational forecasting, adaptive decision-making, and maritime supply chain resilience. Additional studies may also investigate multimodal transportation integration, sustainability-oriented smart-port systems, and real-time risk prediction models to support next-generation intelligent maritime logistics management. Overall, the proposed framework contributes toward the development of intelligent, data-driven, and AI-enabled smart port ecosystems capable of supporting resilient global maritime supply chain operations under increasingly dynamic transportation environments.

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