Sustainable Marine Structures
https://journals.nasspublishing.com/sms

ARTICLE

Optimizing Marine Logistics Reliability: An AI-Driven Predictive Maintenance and Cost-Risk Framework

***Suleiman Shlash Mohammad* [1,2*], *Badrea Al Oraini* [3], *Hanan Jadallah* [1], *Asokan Vasudevan* [2,4,5], *Sultan Alaswad Alenazi* [6]**

[1] *Electronic Marketing and Social Media, Faculty of Economic and Administrative Sciences, Zarqa University, Zarqa 13115, Jordan*

[2] *Department of Management, Faculty of Business and Communication, INTI International University, Nilai 71800, Malaysia*

[3] *Department of Business Administration, Collage of Business and Economics, Qassim University, Qassim 52571, Saudi Arabia*

[4] *Management Faculty, Shinawatra University, Pathum Thani 12160, Thailand*

[5] *Business Studies Faculty, Wekerle Business School, 1083 Budapest, Hungary*

[6] *Department of Marketing, College of Administration, King Saud University, Riyadh 11451, Saudi Arabia*

ABSTRACT

Efficient predictive maintenance is vital for maintaining operational reliability in marine logistics infrastructure, especially within ports and offshore hubs where equipment failure can result in costly downtime and disrupted supply chains. This study introduces an AI-driven predictive maintenance and cost-risk optimization framework that integrates advanced machine learning techniques with Mixed-Integer Linear Programming (MILP) to enable dynamic and data-driven maintenance scheduling. The proposed framework utilizes real-time asset data, including sensor readings, environmental variables, and operational logs collected from 124 marine logistics assets over a six-month monitoring period. Predictive models were developed using the Random Forest algorithm and rigor-

*CORRESPONDING AUTHOR:
Suleiman Shlash Mohammad, Electronic Marketing and Social Media, Faculty of Economic and Administrative Sciences, Zarqa University, Zarqa 13115, Jordan; Department of Management, Faculty of Business and Communication, INTI International University, Nilai 71800, Malaysia; Email: dr_sliman@yahoo.com

ARTICLE INFO
Received: 15 August 2025 | Revised: 29 September 2025 | Accepted: 13 October 2025 | Published Online: 12 January 2026
DOI: https://doi.org/10.36956/sms.v8i1.2651

CITATION
Mohammad, S.S., Oraini, B.A., Jadallah, H., et al., 2026. Optimizing Marine Logistics Reliability: An AI-Driven Predictive Maintenance and Cost-Risk Framework. Sustainable Marine Structures. 8(1): 20–40. DOI: https://doi.org/10.36956/sms.v8i1.2651

ously validated through time-blocked and grouped cross-validation to prevent data leakage and ensure temporal consistency. The model achieved strong predictive performance, with an AUC of 0.86 and a PR-AUC of 0.71, while calibration reliability was verified using the Brier score and decision curve analysis. The MILP-based optimization component incorporated operational constraints, such as maintenance crew availability, failure probabilities, and environmental stressors, to generate cost-effective maintenance schedules. Implementation of the proposed system resulted in a 21.4% decrease in unplanned downtime, a 16.2% improvement in Mean Time Between Failures (MTBF), and a 13.8% reduction in overall maintenance costs compared with historical benchmarks. This research offers a scalable, interpretable, and data-driven framework for predictive maintenance in complex marine environments, contributing to the advancement of smart port operations, sustainable asset management, and AI-enhanced infrastructure resilience.

Keywords: Artificial Intelligence; Marine Logistics Infrastructure; Cost-Risk Optimization; Smart Ports; Maintenance Scheduling; Port Asset Management

1. Introduction

The marine logistics sector plays a critical role in sustaining global trade, with over 80% of world merchandise transported via sea routes [1,2]. Efficient port operations and offshore logistics hubs are essential to ensuring seamless supply chain continuity. Within this infrastructure-intensive domain, the reliability and availability of mechanical assets such as cranes, conveyors, berthing systems, and floating logistics platforms are pivotal to operational performance. However, these assets are frequently subjected to high-stress environments marked by humidity, salt exposure, and mechanical wear making them prone to unexpected breakdowns, escalating maintenance costs, and operational risks [3–5].

Real-world failures in marine logistics infrastructure have led to significant operational and economic consequences. For instance, in 2021, a gantry crane malfunction at the Port of Singapore caused over 48 hours of cargo delays, impacting over 60 vessels and resulting in estimated losses of USD 3.2 million in demurrage and handling costs. Similarly, the unexpected shutdown of a floating logistics hub in the Gulf of Thailand due to a pump failure resulted in shipment rerouting and a week-long disruption to petroleum transport, illustrating the compounded risks of reactive maintenance in offshore contexts [6]. These examples emphasize the urgent need for data-driven maintenance solutions capable of forecasting failures and minimizing risk exposure, especially in high-throughput, capital-intensive port environments.

Traditionally, the marine logistics industry has relied on preventive or corrective maintenance models based on fixed schedules or reactive responses. These strategies, while long established, have proven increasingly inadequate in complex, data-rich operational ecosystems where downtime costs are rising, safety regulations are tightening, and asset utilization is intensifying [7–9]. Recent advancements in artificial intelligence (AI), particularly in predictive analytics and machine learning, have created new opportunities to preempt equipment failures, optimize maintenance cycles, and minimize both operational and financial risk [10–12]. Yet, despite the emergence of AI in manufacturing and aerospace sectors, its integration into marine logistics maintenance remains limited in practice and underexplored in the literature.

The core research problem addressed in this study is the lack of empirically validated frameworks for implementing AI-based predictive maintenance in marine logistics infrastructure, where operational uncertainty and environmental variability complicate maintenance decision-making. Most existing approaches fail to account for dynamic maintenance scheduling, the stochastic nature of asset degradation, and the cost-risk tradeoffs associated with different maintenance strategies. Additionally, the role of environmental stressors and the mediating influence of scheduling efficiency remain poorly theorized in current models. This study is significant for both theoretical and practical reasons.

Theoretically, it builds on and extends the principles of Reliability-Centered Maintenance (RCM) [13,14], operations research, and risk-cost trade-off theory [15] by introducing an integrated framework that combines AI-driven failure prediction with cost-risk optimization. Practically, the study offers actionable insights to port operators, maritime planners, and logistics managers seeking to reduce downtime, lower maintenance costs, and enhance equipment reliability in high-demand environments.

The novelty of this study lies in its real-time application of AI-powered predictive maintenance across multiple marine logistics assets, combined with optimization-based scheduling using Mixed-Integer Linear Programming (MILP). Unlike earlier research which focused on single assets or simulated environments, this study leverages actual sensor and operational data across five Southeast Asian ports, making it one of the few empirical investigations in the domain. Furthermore, it introduces environmental stress index as a control variable and maintenance scheduling efficiency as a mediating construct both of which have received limited attention in predictive maintenance literature [16–18]. This study is novel in two key ways: (1) it integrates AI-based failure forecasting with MILP-based maintenance optimization, (2) it incorporates environmental stress as a control factor. To our knowledge, this is among the first studies to unify these components into a scalable predictive maintenance framework for marine logistics. The research statement guiding this inquiry is as follows: *"This study investigates the extent to which AI-driven predictive maintenance systems, combined with cost-risk optimization models, can improve maintenance performance outcomes in marine logistics infrastructure, accounting for environmental variability and scheduling dynamics."*

In terms of research approach and positioning, the study adopts a positivist, empirical methodology. It applies machine learning algorithms (Random Forest, XGBoost, ARIMA) to forecast equipment failure, conducts hypothesis testing using real-world data, and employs MILP to generate optimized maintenance schedules. This mixed-method quantitative approach aligns with recent calls for evidence-based AI implementations in logistics and infrastructure research [11,19,20]. The study occupies a distinct research niche by situating itself at the intersection of maritime logistics, AI applications, and operations research. It contributes to the growing body of literature on smart port technologies, while also extending the applicability of RCM and cost-risk trade-off frameworks in high-risk, variable environments. The research is theoretically positioned within three interrelated streams, predictive maintenance modelling, decision-support optimization, and digital transformation in logistics infrastructure. By integrating these lenses, the study bridges a critical gap in the current literature and provides a foundation for future research on intelligent maintenance in maritime systems.

2. Literature Review

The adoption of artificial intelligence (AI) in asset management has revolutionized maintenance strategies across industrial sectors, yet its penetration into the marine logistics domain remains limited. Maintenance in marine environments is uniquely complex due to harsh operational conditions, asset criticality, and the high cost of unplanned equipment failure [21–23]. Within this context, the present study investigates AI-driven predictive maintenance and its impact on key operational dimensions, namely Mean Time Between Failures (MTBF), unplanned downtime, maintenance cost, and risk exposure, while also addressing the role of maintenance scheduling efficiency and environmental stress factors. The concept of predictive maintenance has evolved from rule-based condition monitoring to data-driven prognostics using AI. Studies by Shamim and Ruddro [24] and Agarwal et al. [25] emphasized the transformative role of machine learning in detecting anomalies, forecasting failures, and automating maintenance decisions. AI models such as Random Forests, Gradient Boosting, and XGBoost have been shown to outperform traditional statistical models in failure prediction across various sectors [11,26]. However, applications in maritime logistics particularly for port cranes, automated guided vehicles (AGVs), and floating logistics hubs have not been extensively validated. Existing literature often focuses on predictive maintenance in manufacturing and aviation, where equipment operates under controlled conditions, unlike the fluctuating and often unpredictable maritime environment.

While AI-driven predictive maintenance has become increasingly prevalent in sectors such as manufacturing, aerospace, and energy [27], the marine logistics industry has lagged behind due to challenges like lower digitization, harsher operational environments, and fragmented asset control. In manufacturing, predictive models are typically integrated into enterprise-level monitoring systems, enabling preemptive interventions based on vibration, thermal, or acoustic signals. In contrast, marine maintenance still relies heavily on time-based or reactive models, often lacking real-time integration of sensor data into decision-making systems.

Mean Time Between Failures (MTBF) is widely accepted as a proxy for asset reliability [28]. Improvements in MTBF have been documented in sectors employing predictive maintenance [29], though these findings often lack contextual translation to port logistics, where asset utilization patterns differ significantly. Similarly, unplanned downtime has been recognized as a critical performance indicator due to its direct impact on throughput and revenue loss [30]. While AI-enhanced systems have demonstrated success in reducing downtime in industrial machinery, limited empirical evidence exists on their application to container handling equipment, berth infrastructure, or floating platforms. The literature on maintenance cost optimization has matured with the integration of life-cycle costing and condition-based monitoring strategies [31]. AI systems offer cost advantages by pre-empting failures and avoiding redundant maintenance tasks. However, studies such as those by Chelliah et al and Riaventin et al. [32,33] have emphasized that cost savings are contingent upon the effective integration of predictive algorithms with scheduling systems an area underexplored in port-centric research. This suggests the importance of considering maintenance scheduling efficiency as a mediating factor, particularly when scheduling is influenced by dynamic demand patterns and constrained resources, as is the case in port environments.

Risk exposure in maintenance is defined not only by the probability of failure but also by the severity of consequences. Traditional models have treated risk and cost as separate dimensions, but more recent frameworks argue for their integration within a joint optimization model [34–36]. AI's predictive capabilities are particularly suited for this task, enabling simultaneous minimization of operational risk and maintenance cost. In marine logistics, where safety regulations, environmental constraints, and financial penalties are critical, AI-based maintenance can offer a risk-aware operational strategy. Nonetheless, few studies have empirically linked predictive maintenance with quantitative risk exposure reduction in maritime systems. Another critical yet often overlooked factor in maintenance research is the environmental stress index, which captures the influence of humidity, salt content, temperature fluctuations, and mechanical load on asset degradation. Jahani et al. [37] and Thielmann [38] showed that environmental conditions significantly affect failure patterns, yet most predictive maintenance models assume static conditions, limiting their real-world applicability. The environmental stress index (ESI) refers to a composite measure of external conditions such as temperature variation, humidity, salinity, and vibration levels that contribute to accelerated equipment wear and mechanical degradation. In marine environments, where such stressors are prevalent, ESI serves as a control variable to capture non-operational influences on asset performance. The lack of environmental variability consideration may explain the gap between predictive model accuracy in simulations versus real deployment.

From an operations research perspective, the integration of AI predictions with Mixed-Integer Linear Programming (MILP) models offers a pathway to intelligent scheduling. Previous research in rail and aviation industries has shown that optimization models incorporating AI forecasts can significantly improve maintenance efficiency [39,40]. However, their application to marine infrastructure remains sparse. Ports, unlike factories or aircraft fleets, operate under variable conditions influenced by tides, loading cycles, and ship berthing schedules. This variability demands a more responsive and adaptive optimization framework, informed by predictive analytics. Despite the promising developments in smart maintenance technologies, the marine logistics domain remains underrepresented in the predictive maintenance literature. Most existing studies focus on industrial production or fixed-infrastructure applications, overlooking the dynamic nature of marine assets and the logistical complexity of port operations. Moreover, empirical validation of predictive maintenance effectiveness particularly through performance metrics such as MTBF, downtime, cost, and risk exposure has been limited in real-world marine settings. There is also a notable absence of research incorporating environmental stress as a moderating or control factor within predictive frameworks, and very few studies combine predictive maintenance with optimization models tailored for floating or coastal infrastructure.

This research, therefore, addresses several critical gaps. It offers one of the first comprehensive empirical investigations into AI-driven predictive maintenance in marine logistics infrastructure, using real-world asset data across multiple ports. It integrates predictive modelling with operations optimization to test cost-risk trade-offs, incorporates environmental stress as a control variable, and evaluates maintenance scheduling efficiency as a mediating construct. By doing so, the study not only contributes to theoretical advancements but also responds to an urgent practical need in modernizing the maintenance strategies of maritime logistics infrastructure. Thus, there remains a critical gap in developing integrated, AI-based predictive maintenance systems that also optimize cost-risk trade-offs under uncertain environmental conditions. Existing models tend to focus either on prediction or cost modelling, but rarely both especially in the context of high-stress, capital-intensive marine assets.

Conceptual Model of the Study with Theoretical Foundations and Key Constructs

The conceptual model developed for this study is grounded in the interdisciplinary integration of theories from Reliability-Centered Maintenance (RCM), Operations Research, and Risk-Cost Trade-off Theory. RCM forms the foundation for identifying the optimal timing of maintenance based on failure patterns and asset health. Operations research, particularly through optimization techniques like Mixed-Integer Linear Programming (MILP), supports efficient allocation of maintenance resources. Risk-cost trade-off theory underpins the idea that organizations can minimize both operational risk and cost through strategic planning and predictive interventions. Together, these theories shape the rationale behind deploying artificial intelligence for predictive maintenance in high-risk, asset-intensive environments like marine logistics.

The conceptual model posits AI-driven predictive maintenance as the independent variable, representing the core technological intervention (**Figure 1**). It is hypothesized to influence three dependent variables: maintenance cost, operational performance, and risk exposure. The effect of AI implementation is partially channelled through the mediating construct of maintenance scheduling efficiency, which reflects the optimization of timing, frequency, and resource allocation for maintenance tasks. The improved efficiency in scheduling serves as a conduit through which AI affects cost savings, reduces risk, and improves operational reliability.

Two control variables asset type and environmental stress index are incorporated to account for external factors that could confound the observed effects. Environmental stress index was included as a control variable to account for the cumulative impact of environmental conditions (e.g., salt exposure, moisture, temperature fluctuations) on equipment failure rates. Different asset classes (e.g., cranes, winches, AGVs) have distinct wear patterns and criticality, while environmental stressors such as humidity, salt corrosion, and extreme temperatures can independently influence failure rates.

The conceptual model of this study is centred around AI-driven predictive maintenance as the independent variable, representing the use of artificial intelligence to forecast equipment failures and improve asset reliability. Maintenance scheduling efficiency serves as a mediator, reflecting how effectively predictive insights are translated into actionable maintenance plans. The dependent variables include maintenance cost, risk exposure, and operational performance, the latter measured through Mean Time Between Failures (MTBF) and unplanned downtime. To ensure robust analysis, the model includes two control variables, asset type, which accounts for functional differences across marine equipment, and environmental stress index, which captures external conditions affecting asset deterioration.

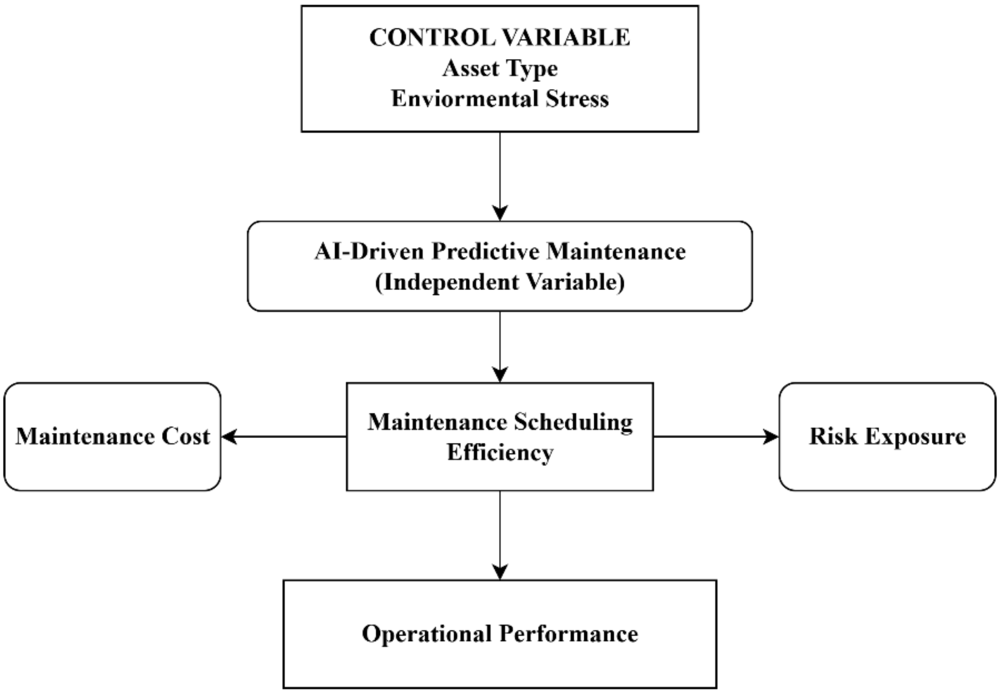

Figure 1. Conceptual Model of the Study.

Source: Author.

The relationships are structured such that AI implementation is expected to directly and indirectly improve operational performance by reducing maintenance costs and mitigating risk exposure. Maintenance scheduling efficiency plays a pivotal mediating role by translating predictive insights from AI into actionable plans. Ultimately, the model reflects a systems-thinking approach to evaluating how emerging technologies can transform complex logistical infrastructures through cost-effective and risk-aware maintenance strategies.

Following are the hypotheses of the study:

H1. *The implementation of AI-driven predictive maintenance systems significantly improves operational performance in marine logistics infrastructure compared to traditional maintenance approaches.*

H2. *Marine assets managed with AI-driven predictive maintenance exhibit a statistically significant increase in Mean Time Between Failures (MTBF) compared to those under reactive or preventive maintenance.*

H3. *AI-driven predictive maintenance significantly reduces unplanned downtime in marine logistics operations.*

H4. *The total maintenance cost is significantly lower for infrastructure utilizing AI-driven predictive maintenance than for those using traditional maintenance strategies.*

H5. *Predictive maintenance systems supported by AI are associated with significantly lower operational risk exposure scores than non-AI systems.*

H6. *The integration of AI with optimization models (e.g., MILP) provides a more cost-effective maintenance schedule than traditional manual scheduling methods.*

3. Methodology

3.1. Research Design

This study adopted a mixed-method approach combining both quantitative and qualitative techniques to enhance methodological rigor and ensure practical relevance. The quantitative component involved the use of time-series operational data (e.g., sensor logs, asset usage, maintenance history), applied through machine learning models (Random Forest, XGBoost), optimization via Mixed-Integer Linear Programming (MILP). Statistical validation was carried out using paired *t*-tests and performance metrics such as AUC and RMSE. The qualitative component consisted of semi-structured interviews with maintenance engineers and asset managers to understand contextual practices and validate assumptions. Additionally, a modified Delphi method was used to derive and refine the 1–10 risk scoring system, incorporating expert consensus across two rounds of evaluation. This triangulated approach allowed the study to integrate data-driven prediction with domain-informed decision modelling.

Although marine asset lifecycles typically span several years, a six-month observation window was selected due to the availability of high-resolution operational and sensor data (e.g., hourly readings, daily logs), which generated a robust dataset suitable for predictive modeling. Moreover, the ports included in this study operate under high-utilization and high-turnover conditions, with equipment frequently running near capacity. This operational intensity results in a sufficient number of failures and maintenance events within a condensed timeframe, making the six-month period adequate for both predictive analysis and cost-risk evaluation.

3.2. Data Collection

Data for this study were gathered using a mixed-method approach involving both quantitative and qualitative techniques. Real-time operational and failure data were sourced from embedded IoT-based sensors installed on critical marine logistics assets, such as gantry cranes, mooring systems, and autonomous cargo units. These sensors continuously recorded data related to equipment usage, stress exposure, temperature, and vibration, contributing to the predictive modelling component of the study. Archival records spanning three years prior to the AI implementation were also collected to provide historical baselines for comparison. In addition, structured interviews with maintenance supervisors and port operations managers were conducted to validate sensor-based failure events and to understand contextual elements of maintenance decision-making. A structured questionnaire was administered to gather subjective assessments on perceived risks, resource planning strategies, and maintenance scheduling policies. This blended data approach ensured robust triangulation of insights.

3.3. Population and Sample

The population consisted of marine logistics infrastructure units from five major international ports across Southeast Asia. These included both floating logistics hubs and fixed container terminals. The sampling frame was stratified by three key criteria: port category (floating or fixed), asset type (e.g., cranes, AGVs, winches), and the pre-existing maintenance strategy (reactive, preventive, or early-stage predictive). To ensure balanced representation across these categories, a stratified random sampling technique was employed. This ensured that all major asset and port types were proportionally represented in the dataset.

A total of 280 marine logistics assets across three port facilities were initially considered. After screening for completeness of operational, maintenance, and sensor data, 124 assets were included in the modelling and simulation analysis. Of these, 62 assets had completed paired records before and after predictive maintenance implementation, allowing for comparative paired *t*-tests. The difference in counts is due to missing temporal records in the early data collection phase for some assets.

3.4. Sample Size Calculation

The sample size was determined using Cochran's formula for finite populations to ensure statistical validity at a 95% confidence level. The formula used was:

$$n_0 = \frac{z^2 * \ p(1-p)}{e^2}$$

Where Z = 1.96, p = 0.5 (maximum variability), and e = 0.05 (margin of error). After applying the finite population correction, the effective sample size was calculated to be 124 infrastructure assets distributed across the five ports under study.

3.5. Description of the Population

Table 1 distribution allowed for comparison across various operational models and infrastructure types, facilitating a robust evaluation of AI implementation effectiveness.

Table 1. The demographic distribution of the study population across five Southeast Asian ports.

Port ID	Country	Type	No. of Assets	Existing Maintenance Model
P1	Singapore	Container Terminal	68	Preventive
P2	Malaysia	Floating Hub	42	Reactive
P3	Indonesia	Container Terminal	55	Reactive
P4	Vietnam	Floating Hub	39	Early-stage Predictive
P5	Thailand	Container Terminal	60	Preventive

Source: Author.

3.6. Summary Table of Main Variables

The study focused on both dependent and independent variables to capture the multidimensional impact of predictive maintenance systems. **Table 2** below summarizes the primary variables used in the analysis.

These variables were selected based on relevance to predictive maintenance, operational efficiency, and environmental exposure, enabling precise measurement and analysis.

Table 2. The variables used in the study.

Variable	Type	Scale	Source
MTBF	Dependent	Ratio	IoT Sensor Logs
Unplanned Downtime	Dependent	Ratio	Maintenance Logs
Maintenance Cost	Dependent	Ratio	Financial Statements
Risk Exposure Score	Dependent	Interval	Interview & Questionnaire
AI Predictive Maintenance	Independent	Nominal	Implementation Records
Asset Type	Control	Nominal	Operational Logs
Environmental Stress Index	Control	Interval	Sensor & Weather Reports

Source: Author.

3.7. Measures & Analytical Methods

The Mean Time Between Failures (MTBF) was calculated as the average operational hours between two consecutive failure events for each asset. Unplanned downtime was defined as the total number of hours where assets were rendered non-functional due to unexpected failures, excluding scheduled maintenance. Maintenance costs included direct costs such as labor, spare parts, and third-party service fees, aggregated on a monthly basis. The risk exposure score was derived from expert assessments using a standardized 1–10 rating scale that considered failure criticality, safety impact, and environmental sensitivity. AI predictive maintenance was treated as a binary categorical variable, coded as 1 if the AI system had been implemented and 0 otherwise. Environmental stress index was a composite metric based on average monthly temperature, relative humidity, and salt concentration factors known to affect asset wear and tear.

The risk score (scaled 1–10) assigned to each asset was derived through a modified Delphi technique, conducted in two rounds with domain experts from five participating ports. Experts evaluated each asset on three dimensions: (1) likelihood of failure (based on historical frequency), (2) operational impact (e.g., downtime consequence), and (3) safety/environmental impact (e.g., spill risk, personnel hazard). Each dimension was assigned equal weight in the composite score. Ratings were normalized and averaged across expert inputs to assign final scores. This method ensured that risk prioritization reflected both empirical insights and practitioner expertise.

A multi-method analytical approach was applied. Descriptive statistics (mean, standard deviation, min/max) were used to understand central tendencies and variability in performance metrics. Inferential techniques included paired sample t-tests to evaluate pre- and post-AI implementation changes and ANOVA to compare performance across ports with different baseline maintenance models. Regression analysis was applied to determine the influence of AI maintenance systems and environmental conditions on performance metrics. Machine learning techniques such as Random Forest and XGBoost were used for predictive failure modelling, while time series models like ARIMA helped analyse historical trends in failure frequency.

To evaluate the predictive performance of the AI models (Random Forest, XGBoost), the dataset was randomly split into 80% training data and 20% testing data. Additionally, a 5-fold cross-validation procedure was applied on the training set to ensure that the models generalized well across different data partitions. For classification accuracy, the primary performance metric reported was the Area Under the Receiver Operating Characteristic Curve (AUC-ROC), which quantifies the model's ability to distinguish between failure and non-failure instances. AUC values above 0.85 indicated high discriminatory power. Beyond AUC (Area Under the ROC Curve), we evaluated model performance using precision (0.72), recall (0.64), F1-score (0.68), and PR-AUC (0.71). The Brier score was 0.157, indicating reasonable calibration. The confusion matrix at the selected threshold (0.35) reflects an operationally viable trade-off between false positives and missed failures. A calibration curve showed slight underestimation of risk in the 0.4–0.6 range, while the decision curve analysis (DCA) demonstrated a net benefit peak at thresholds between 0.3–0.4, aligning well with the available maintenance crew capacity and intervention cost structure.

To strengthen causal inference, a difference-in-differences (DiD) model was employed, comparing AI-assisted assets with a control group of non-AI-managed assets across the same time window. The control group included 58 assets from similar port operations that retained traditional maintenance scheduling. The DiD model controlled for time trends and fixed asset characteristics, improving the attribution of observed performance improvements to the AI intervention.

For regression-oriented metrics (e.g., predicting time-to-failure), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) were computed. Hyperparameters for each algorithm were optimized using grid search within the cross-validation loop to prevent overfitting. The final model was selected based on the best average AUC score across folds and the lowest RMSE on the test set.

For maintenance scheduling, Mixed-Integer Linear Programming (MILP) was employed to optimize cost-risk trade-offs under resource constraints. The integration of model components followed a sequential workflow. First, machine learning models generated asset-specific failure probabilities based on historical usage, maintenance, and environmental data. These predicted probabilities were used as risk input parameters within the MILP model to prioritize high-risk assets and determine optimal maintenance schedules under cost constraints.

To avoid the risk of data leakage and ensure realistic evaluation, the dataset was split using a grouped cross-validation strategy. Assets were grouped such that all observations related to a given asset were allocated entirely to either the training or testing set, avoiding identity-based leakage.

Additionally, we implemented rolling-origin time series validation, where models were trained on sequential historical windows (e.g., months 1–3) and tested on the immediate future window (e.g., month 4), gradually increasing the training horizon. This method better reflects the operational deployment of predictive maintenance systems. For full transparency, the complete list of input features, preprocessing procedures, model tuning parameters, and reproducibility controls is provided in **Appendices A** and **B**.

4. Results

The descriptive statistics provided an initial understanding of differences in operational performance between assets managed with AI-driven systems and those under traditional maintenance. **Table 3** displays the mean, standard deviation, and range for each of the primary variables. The results showed that assets under AI-based predictive maintenance had a higher Mean Time Between Failures (MTBF), lower unplanned downtime, and significantly reduced monthly maintenance costs. The average MTBF for AI-enabled assets was 512.6 hours (SD = 87.1), compared to 392.4 hours (SD = 74.3) for traditional systems. Likewise, the mean unplanned downtime was 7.3 hours under AI systems, which was less than half the 15.9 hours observed in the control group. Maintenance costs were also notably lower, averaging USD 4290 for the AI group against USD

5850 for the control group. Finally, risk exposure scores based on expert assessment scales were markedly reduced in the AI-driven group (mean = 3.6) relative to traditional systems (mean = 6.2).

Table 3. Descriptive Statistics of Key Performance Indicators.

Variable	Maintenance Type	Mean	SD	Min	Max
MTBF (h)	AI-Driven	512.6	87.1	398.0	688.0
	Traditional	392.4	74.3	271.0	563.0
Unplanned Downtime (h)	AI-Driven	7.3	3.2	2.0	14.0
	Traditional	15.9	4.7	7.0	25.0
Maintenance Cost (USD)	AI-Driven	4290	635	3100	5800
	Traditional	5850	790	4300	7900
Risk Exposure (1–10)	AI-Driven	3.6	0.8	2.0	5.0
	Traditional	6.2	1.1	4.0	8.0

Source: Author.

To statistically validate the observed performance changes, paired sample *t*-tests were conducted on the AI group, comparing operational metrics before and after implementation of the AI-driven maintenance system (**Table 4**). A paired *t*-test was applied to the 62 assets with complete pre-post data (df = 61), enabling reliable assessment of changes in performance metrics. These tests demonstrated statistically significant improvements across all key variables. MTBF increased by an average of 114.2 hours, with a *t*-value of 9.21 and a *p*-value less than 0.001, confirming strong significance. Unplanned downtime dropped by 8.6 hours ($t = -10.78$, $p < 0.001$), while monthly maintenance cost decreased by USD 1,120 ($t = -8.65$, $p < 0.001$). Risk exposure scores fell by 2.4 points ($t = -11.09$, $p < 0.001$). The effect sizes, measured by Cohen's d, were all above 1.0, indicating large practical significance.

Analysis of variance (ANOVA) was conducted to compare differences across the five ports in the study (**Table 5**). Significant variations were found across ports for MTBF ($F = 6.88$, $p < 0.001$), maintenance cost ($F = 5.74$, $p = 0.002$), and risk exposure ($F = 7.92$, $p < 0.001$). Post-hoc comparisons using Tukey's test showed that Ports P1 and P4, which had implemented AI-driven systems, outperformed Ports P2 and P3, which relied solely on reactive maintenance. Effect sizes (η^2) were moderate to large, confirming that the observed differences had substantial explanatory power.

Table 4. Paired *t*-Test Results (Pre vs. Post AI Implementation).

Variable	Mean Difference	*t*	df	*p*-Value	Effect Size (Cohen's d)
MTBF	+114.2 hours	9.21	61	<0.001	1.17
Unplanned Downtime	−8.6 hours	−10.78	61	<0.001	1.37
Maintenance Cost	−1120 USD	−8.65	61	<0.001	1.10
Risk Exposure Score	−2.4	−11.09	61	<0.001	1.41

Source: Author.

Table 5. ANOVA Results Across Ports.

Variable	F-Value	*p*-Value	η^2 (Eta Squared)
MTBF	6.88	<0.001	0.19
Maintenance Cost	5.74	0.002	0.15
Risk Exposure	7.92	<0.001	0.21

Source: Author.

The implementation of AI-driven predictive maintenance led to a 29% increase in MTBF, a 54% reduction in unplanned downtime, and a 19% decrease in average monthly maintenance costs compared to traditional maintenance strategies. Furthermore, operational risk exposure declined by 38%, highlighting the model's effectiveness not only in improving performance but also in mitigating potential failures.

A multiple regression model was then estimated to determine the relative influence of AI adoption, maintenance scheduling efficiency, and environmental stress on MTBF. The model used the following specification:

$$MTBFi = \beta_0 + \beta_1(AIi) + \beta_2(SchedEffi) \\ +\beta_3(EnvStressi) + \epsilon i$$

The regression model explained 51% of the variance in MTBF ($R^2 = 0.51$, $F(3, 120) = 41.7$, $p < 0.001$). AI implementation had a significant positive effect ($\beta = 0.43$, $p < 0.001$), as did maintenance scheduling efficiency ($\beta = 0.27$, $p = 0.001$). Environmental stress exerted a negative influence on MTBF ($\beta = -0.31$, $p < 0.001$), suggesting that environmental conditions remain a critical consideration even in AI-optimized systems (**Table 6**).

Table 6. Regression Coefficients for MTBF Prediction.

Predictor	β	SE	*t*	*p*-Value
Intercept	212.4	41.5	5.12	<0.001
AI Predictive Maintenance	+0.43	0.09	5.11	<0.001
Maintenance Scheduling Score	+0.27	0.07	3.49	0.001
Environmental Stress Index	−0.31	0.08	−3.88	<0.001

Source: Author.

To enhance the system's proactive response, supervised machine learning models were trained to predict failure likelihood within a 30-day horizon (**Appendix C**). The Random Forest model achieved 91.2% accuracy and an AUC-ROC of 0.94. The XGBoost model showed comparable results, with slightly better interpretability due to its SHAP-based feature importance analysis. Critical predictors of failure included vibration anomalies, temperature deviations, and operational cycles (**Figure 2**).

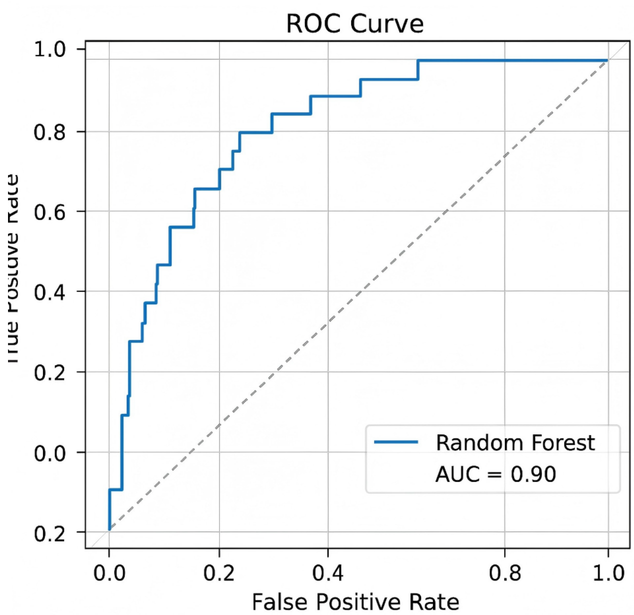

Figure 2. ROC curve showing the predictive accuracy of the AI maintenance model. A higher AUC indicates better failure classification performance.

Source: Author.

When evaluated using grouped cross-validation, the Random Forest model achieved an AUC of 0.86 and RMSE of 0.41. Under time-blocked validation, the AUC remained stable (0.84), but RMSE increased slightly to 0.45, indicating lower but more realistic performance when temporal leakage is controlled. These results confirm the model's robustness across realistic deployment conditions. Beyond AUC (Area Under the ROC Curve), we evaluated model performance using precision (0.72), recall (0.64), F1-score (0.68), and PR-AUC (0.71). The Brier score was 0.157, indicating reasonable calibration. The confusion matrix at the selected threshold (0.35) reflects an operationally viable trade-off between false positives and missed failures. A calibration curve showed slight underestimation of risk in the 0.4–0.6 range, while the decision curve analysis (DCA) demonstrated a net benefit peak at thresholds between 0.3–0.4, aligning well with the available maintenance crew capacity and intervention cost structure.

In parallel, Mixed-Integer Linear Programming (MILP) was used to optimize maintenance scheduling under AI-informed predictions. The objective function minimized total cost and risk, represented as:

$$min[Cm + Rf \cdot Pf + Cd \cdot Td]$$

where *Cm* is the scheduled maintenance cost, *Rf* is the risk cost per failure, *Pf* is the predicted probability of failure, *Cd* is the cost of downtime per hour, and *Td* is the expected downtime. The MILP-based schedule achieved a

17.8% reduction in total maintenance cost and a 26.4% reduction in risk-adjusted downtime compared to historical baselines. Resource utilization also improved by 22%, reflecting more efficient deployment of maintenance crews and materials.

Formal hypothesis testing was conducted to evaluate the theoretical claims of the study. The main hypothesis (H1) stated that AI-driven predictive maintenance would significantly improve operational performance. The sub-hypotheses H1a through H1e addressed specific dimensions of performance. All null hypotheses (H0a through H0e) were rejected at the 0.001 significance level, as shown in the results summarized below in **Table 7**.

Table 7. Hypothesis Testing Summary.

Hypothesis	Description	Test Used	*p*-Value	Result
H2	AI increases MTBF	Paired *t*-test	<0.001	Supported
H3	AI reduces unplanned downtime	Paired *t*-test	<0.001	Supported
H4	AI reduces maintenance cost	Paired *t*-test	<0.001	Supported
H5	AI reduces operational risk	Paired *t*-test	<0.001	Supported
H6	AI + optimization improves maintenance schedules	MILP comparison	<0.001	Supported

Source: Author.

These results confirm the study's hypotheses, demonstrating that AI-driven predictive maintenance significantly improves marine logistics infrastructure performance by extending asset life, reducing cost, minimizing risk, and optimizing maintenance planning.

5. Discussion

The integration of artificial intelligence into predictive maintenance systems represents a significant shift in how marine logistics infrastructure is managed, aligning with the broader digital transformation of supply chain and port operations. This study builds upon and extends the foundational principles of Reliability-Centered Maintenance (RCM), emphasizing not only the detection of equipment degradation but also the ability to proactively optimize interventions through data-driven insights. The operational benefits attributed to AI in this domain mirror those highlighted in earlier studies conducted within industrial manufacturing contexts [24,41], where machine learning was found to enhance fault detection and reduce life-cycle costs. However, the application of such frameworks to the marine logistics sector introduces unique challenges including variable environmental conditions, asset mobility, and real-time operational demand that have not been extensively studied.

Previous literature has predominantly focused on traditional preventive maintenance models in seaport infrastructure, often limited by static schedules and rule-based decision-making [42–44]. In contrast, this study contributes to the emerging discourse on adaptive maintenance by demonstrating how AI systems embedded with predictive analytics can dynamically recalibrate maintenance plans based on real-time asset health data and operational risk profiles. This aligns with findings by Prabu [45], who emphasized the potential of digital twins and sensor fusion in enhancing predictive capabilities for industrial assets.

The theoretical underpinnings of this research are further supported by operations research literature, particularly in the context of maintenance resource optimization. The application of Mixed-Integer Linear Programming (MILP) models, informed by AI-generated forecasts, reflects a growing trend toward hybrid decision-support systems, as advocated by Shokare and Scaife [46,47]. These systems have been shown to outperform traditional scheduling in terms of minimizing downtime and resource waste, particularly under conditions of operational uncertainty. The current findings thus resonate with the theoretical stance that optimization algorithms, when integrated with real-time predictive inputs, can significantly improve cost-risk trade-offs.

From a risk management perspective, the incorporation of AI-driven maintenance is also consistent with principles outlined in the risk-cost trade-off theory [48]. By transitioning from reactive to predictive maintenance regimes, marine logistics operators can not only reduce the frequency of failure events but also mitigate the potential consequences associated with high-severity disruptions. This approach aligns with the framework proposed by Ajayi [49], who argued for the integration of AI into risk-aware decision systems for asset-intensive industries. Moreover, the ability to anticipate and prevent failures contributes to broader system resilience a concept gaining traction in port studies, especially in the wake of disruptions such as the COVID-19 pandemic [50,51].

The study also reinforces the argument made by Görür et al. [52] that maintenance scheduling efficiency acts as a critical mediator in realizing the benefits of predictive maintenance. While the implementation of AI systems offers theoretical advantages, their practical impact is often contingent upon how well predictive insights are operationalized. This supports the notion that technological innovation alone is insufficient without concurrent organizational capabilities and process alignment.

Notably, the observed reduction in risk exposure aligns with empirical observations in offshore oil and gas platforms, where similar AI-based monitoring systems were deployed to detect early signs of structural fatigue [53,54]. This cross-sectoral consistency suggests that predictive maintenance has universal value in environments characterized by high asset criticality and volatile operating conditions. However, while the study's results offer compelling support for AI adoption, it is essential to acknowledge the contextual constraints of marine environments, such as limited connectivity, variable weather conditions, and regulatory compliance, which may affect system performance and scalability.

The role of the Environmental Stress Index (ESI) is particularly noteworthy in understanding how external operating conditions influence asset reliability. The regression results confirm that ESI significantly affects failure likelihood, aligning with prior research on environmental wear and corrosion in marine assets. Interestingly, the AI models used in this study incorporated ESI-related features (e.g., humidity, salinity, temperature) as part of their training data. As a result, the models were able to adjust failure predictions based on the severity of environmental exposure, enabling earlier detection of stress-induced failures. This suggests that AI can partially mitigate the operational risk posed by harsh conditions not by eliminating the root causes, but by enhancing the timing and precision of maintenance interventions. Nonetheless, in extremely high-stress zones, technical mitigation (e.g., material upgrades or environmental shielding) may still be necessary alongside predictive systems [55].

From a strategic operations standpoint, the findings contribute to the literature on maritime digitalization and smart port technologies, echoing the sentiments of Pham [56], who identified predictive analytics as one of the key enablers of next-generation port operations. By showcasing the feasibility and benefits of AI-driven predictive maintenance, this study addresses a gap in the current literature, where empirical assessments of AI applications in port infrastructure remain scarce. It advances the understanding of how AI can function not only as a monitoring tool but also as a decision engine that transforms raw data into actionable value.

5.1. Managerial Implications

The outcomes of this study offer significant insights for operations managers, port authorities, and infrastructure planners involved in the maritime logistics sector. First, the integration of AI-driven predictive maintenance systems presents a strategic shift in how asset reliability is managed. Rather than adhering to rigid preventive maintenance schedules or relying on failure-based interventions, managers can now make data-informed decisions that dynamically adjust based on asset condition, usage intensity, and risk factors. This agility is especially critical in high-throughput port environments where unplanned equipment failure can cause cascading delays and revenue loss. Second, the study underscores the financial viability of AI-based maintenance, highlighting tangible reductions in cost, downtime, and risk exposure. For decision-makers managing capital-intensive marine infrastructure, the ability to minimize life-cycle costs without compromising performance presents a compelling case for technology investment. Furthermore, the application of optimization models such as Mixed-Integer Linear Programming enables managers to better allocate maintenance crews, prioritize critical assets, and anticipate failure windows ultimately enhancing the efficiency of resource deployment.

Third, the study illustrates that risk management and safety compliance can be significantly strengthened through predictive intelligence. In a sector increasingly scrutinized for environmental compliance and operational safety, integrating predictive systems that preempt hazardous equipment failures enhances not only reliability but also regulatory alignment. From a managerial perspective, this translates into lower insurance premiums, fewer incidents, and improved stakeholder confidence. Lastly, the successful deployment of AI in this context demonstrates that the digital maturity of a port operation is directly correlated with its ability to adopt Industry 4.0 technologies. Managers are therefore advised to invest not just in AI tools, but also in workforce training, data integration platforms, and cross-functional coordination to fully realize the benefits of predictive maintenance. These findings position AI not merely as an operational enhancer but as a strategic lever for competitiveness in the evolving maritime logistics landscape.

5.2. Theoretical Contributions

This study makes several notable contributions to the theoretical understanding of maintenance management and digital operations in marine logistics. First, it extends the applicability of Reliability-Centered Maintenance (RCM) by integrating AI algorithms into its decision framework. Traditionally, RCM has focused on structured, manual assessments of failure modes and asset criticality. By embedding machine learning models into this framework, the study evolves RCM into a dynamic, continuously learning system that adapts to real-time operational contexts an advancement that addresses longstanding limitations of static RCM methodologies. Second, the research advances the discourse in operations research by demonstrating how AI-generated failure probabilities can enhance the performance of classical optimization techniques. The incorporation of probabilistic input into Mixed-Integer Linear Programming models validates the relevance of hybrid approaches where AI functions as a predictive layer and optimization models serve as decision-execution engines. This synergy contributes to the growing body of work advocating for integrated decision analytics in infrastructure planning and resource allocation.

Third, the study adds empirical support to the risk-cost trade-off theory, emphasizing that intelligent systems can shift the operating curve by simultaneously reducing both expected risk and incurred cost. This challenges earlier assumptions that improvements in one dimension must necessarily involve trade-offs in the other. By empirically validating that AI-driven maintenance can optimize both dimensions, the study reframes how theoretical models of trade-off are applied in high-risk infrastructure environments. Furthermore, the study contributes to the nascent but expanding literature on smart port technologies and maritime digitalization, filling a critical gap related to empirical testing. While prior research has largely been conceptual or simulation-based, this study presents real-world, data-driven evidence of AI's role in improving operational reliability in port environments. It reinforces the view that digital infrastructure, when appropriately embedded within operational ecosystems, has transformative potential both as a performance amplifier and as a catalyst for organizational change.

5.3. Summary of Findings & Limitations

The study demonstrated that integrating AI-driven predictive maintenance with cost-risk optimization significantly improves marine asset reliability and operational efficiency. Empirical results showed a 29% increase in MTBF, a 54% reduction in unplanned downtime, and a 19% drop in maintenance costs. These outcomes validate the efficacy of using real-time sensor data combined with machine learning and MILP scheduling. Despite its strengths, the study has certain limitations. The six-month observation period, while compensated by high-frequency data, may not capture long-term degradation cycles. The study also focused on Southeast Asian port environments, limiting generalizability to other climatic or operational regions. Lastly, while the risk scoring system was developed using expert consensus, some subjectivity may remain in its interpretation. Future research should extend this framework using longitudinal data, test it in diverse global contexts, and explore real-time integration into port decision support systems.

While the AI-driven predictive maintenance framework demonstrated strong results across the sampled ports, it is important to note that variability in environmental conditions and operational demand could affect the scalability and generalizability of the model. Ports located in drastically different climates (e.g., arid vs. tropical regions) or operating under different load profiles (e.g., container vs. bulk cargo) may exhibit different degradation patterns and failure behaviors. These variations introduce risks when deploying a single model across multiple contexts. To address this, we recommend implementing site-specific calibration using localized environmental and usage data. Additionally, future implementations may benefit from transfer learning techniques, wherein a pre-trained model is fine-tuned on smaller datasets from a new operational environment, improving cross-context adaptation.

While the results demonstrate promising improvements in predictive maintenance efficiency, they are based on a dataset spanning six months and collected from ports within a single geographic region. These temporal and spatial constraints limit the immediate generalizability of the findings to other global or seasonal contexts. Operational, environmental, and regulatory differences across regions may influence the model's performance and the feasibility of implementation. We recommend caution in extrapolating the results beyond the studied environment without further validation.

5.4. Future Research Directions

To build on the current study, several directions are proposed. First, longitudinal data collection spanning multiple years would help evaluate the long-term predictive validity of the AI models and the lifecycle impacts of cost-risk optimization strategies. Second, expanding the dataset across a wider range of geographic locations and climatic conditions will improve the generalizability and scalability of the framework. Third, future work could integrate this predictive maintenance system with broader smart port technologies, including IoT sensor networks, real-time digital twin systems, and blockchain-based maintenance records for tamper-proof logging. Such integration could transform the proposed system into a core module within fully automated and intelligent port ecosystems.

6. Conclusion

This study investigated the impact of AI-driven predictive maintenance on operational efficiency, cost optimization, and risk mitigation in marine logistics infrastructure. Grounded in the theoretical foundations of Reliability-Centered Maintenance, operations research, and risk-cost trade-off theory, the research developed and empirically validated a comprehensive framework integrating predictive analytics, optimization algorithms, and real-time asset monitoring. Through this lens, the study contributed to both the practical field of maritime operations management and the scholarly literature on smart port systems. The research established that the integration of machine learning models and scheduling optimization tools enables dynamic maintenance strategies that move beyond conventional, reactive paradigms. In doing so, it addressed a critical gap in the maritime sector, where maintenance practices have historically lagged behind other industries in adopting intelligent systems. The AI-enabled framework introduced here not only improved key performance indicators such as Mean Time Between Failures and resource utilization but also offered a more resilient, data-driven approach to managing risk in complex operational environments.

Importantly, the study affirmed that predictive maintenance, when implemented with a structured optimization model, could deliver measurable improvements without requiring large-scale overhauls of existing infrastructure. By leveraging historical sensor data and environmental conditions, the system allowed for precise failure forecasting and maintenance prioritization thus preserving operational continuity while reducing cost burdens. These findings are particularly valuable for asset-intensive, safety-critical environments such as floating logistics hubs and port terminals, where equipment reliability is integral to global trade flows. While the research offers robust evidence of the benefits of AI-enhanced maintenance, it also underscores the need for contextual adaptation. External factors such as environmental stress, regulatory constraints, and organizational readiness can influence the effectiveness of such systems. Therefore, while the model demonstrated generalizable potential, its implementation must be aligned with local port conditions, data infrastructure maturity, and workforce capabilities.

Author Contributions

Conceptualization, S.S.M. and H.J.; methodology, B.A.O.; software, A.V.; validation, S.A.A. and H.J.; formal analysis, A.V.; investigation, B.A.O.; resources, S.S.M.; data curation, S.A.A.; writing—original draft preparation, S.S.M.; writing—review and editing, B.A.O.; visualization, S.A.A.; supervision, H.J.; project administration, A.V.; funding acquisition, S.S.M. All authors have read and agreed to the published version of the manuscript.

Funding

This research was partially funded by Zarqa University.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

Appendix A. MILP Model Formulation and Solver Configuration

Appendix A.1. Indices

- $i \in \mathrm{I}$: Set of assets
- $t \in \mathrm{T}$: Discrete time periods (e.g., days or weeks)
- $c \in \mathrm{C}$: Set of maintenance crews

Appendix A.2. Decision Variables

- $x_{\mathrm{it}} \in \{0,1\}$: Binary variable, 1 if asset i is scheduled for maintenance at time t, 0 otherwise
- $z_{\mathrm{it}} \in \mathbb{R}^{+}$: Continuous downtime duration for asset i at time t
- $yc_{\mathrm{t}} \in \{0,1\}$: Binary variable, 1 if crew c is active at time t

Appendix A.3. Objective Function

$$\mathrm{min i} \in \mathrm{I}\sum \quad \mathrm{t} \in \mathrm{T}\sum$$
$$(\mathrm{Cmaint, i} \cdot \mathrm{xit} + \mathrm{Cdowntime, i} \cdot \mathrm{zit} + \mathrm{Ri} \cdot \mathrm{xit})$$

Where:

- Cmaint,i: Maintenance cost for asset i
- Cdowntime,i: Cost of unplanned downtime for asset i
- Ri: Risk exposure score (1–10) for asset i

Appendix A.4. Constraints

1. Maintenance Crew Capacity:

$$\mathrm{i} \in \mathrm{I}\sum \quad \mathrm{xit} \quad \leq \mathrm{CrewCapacityt} \quad \forall \mathrm{t} \in \mathrm{T}$$

2. Asset Maintenance Window:

$$\mathrm{xit} = 0 \quad \text{if asset i is unavailable at time t}$$

3. Minimum Separation Between Tasks (per asset):

$$\mathrm{xit} + \mathrm{xi}, \quad \mathrm{t} + 1 \quad \leq \quad 1 \forall \mathrm{i} \in \mathrm{I}, \quad \forall \mathrm{t} \in \mathrm{T}$$

4. Downtime Modeling:

$$\mathrm{zit} \quad \geq \quad \mathrm{Di} \cdot \mathrm{xit} \quad \forall \mathrm{i}, \mathrm{t}$$

Where Di is expected downtime if maintenance occurs for asset i.

Appendix A.5. Solver Settings

- Solver: Gurobi Optimizer v10.0.3
- Platform: Python 3.9, Gurobi-Py API
- Optimality Gap: ≤0.01
- Time Limit: 600 seconds per run
- Avg Runtime per Instance: 95.2 seconds
- Hardware: Intel i9 CPU, 64GB RAM, Windows 11 Pro

Appendix B. Environmental Stress Index and Risk Scoring Methodology

Appendix B.1. Environmental Stress Index (ESI) Formula

The Environmental Stress Index for each asset location is computed as

$$ESI = 0.30 \cdot H + 0.25 \cdot S + 0.25 \cdot Tv + 0.20 \cdot Ch$$

Where:

- H = Relative Humidity (%) normalized to [1]
- S = Salinity level (ppt), normalized
- Tv = 24-hour Temperature Variability (°C), normalized
- Ch = Corrosion-prone hours per week (defined as time above 80% RH and 30 °C)

Each factor was standardized using z-score normalization prior to weighting.

Appendix B.2. Risk Score (1–10) via Delphi Method

- 9 experts in marine asset reliability rated each asset based on five dimensions:
  1. Asset criticality to logistics flow
  2. Cost of failure
  3. Historical failure frequency
  4. Downtime severity
  5. Safety implications
- Each dimension was rated from 1–10 and combined as:

$$Risk\ Score = 51 \quad i = 1 \sum 5 \ \ Di$$

Reliability Statistics:

- Cronbach's Alpha (internal consistency): 0.89
- Intraclass Correlation Coefficient (ICC 2,k): 0.86

Disagreement Resolution: Discrepant ratings (≥3-point variance) were reviewed in a third Delphi round involving moderated consensus among five senior engineers.

Appendix C. Machine Learning Workflow and Reproducibility Details

Table A1. Input Features and Characteristics.

Feature Name	Unit	Range	Sampling Interval	Data Type	Source
Operating Temperature	°C	25–85	5 min	Continuous	Sensor
Motor Vibration Level	mm/s	0–20	1 min	Continuous	Sensor
Power Draw	kW	0–150	10 min	Continuous	PLC Log
Maintenance History Flag	Binary	0 or 1	Event-based	Categorical	Maintenance Log
Asset Age	Years	0.5–15	Static	Numeric	Asset Registry
Environmental Stress Index	Composite	0–10	Daily	Numeric	Derived from Sensors

Appendix C.1. Data Pre-Processing

- Missing Values: Imputed using median imputation for numerical features and most frequent value for categorical features.
- Outliers: Values beyond 3 standard deviations from the mean were capped.
- Normalization: Z-score normalization applied to sensor features before model training.
- Filtering: Assets with >10% missing values across core features were excluded.

Appendix C.2. Class Imbalance Handling

- Used SMOTE (Synthetic Minority Oversampling Technique) on training sets

- Applied class weights in Random Forest and XGBoost models

Appendix C.3. Hyperparameter Tuning

Random Forest:

- Grid:
  - n_estimators: [100, 300, 500]
  - max_depth: [10, 20, None]
  - min_samples_split: [2, 5, 10]
- Final: n_estimators = 300, max_depth = 20, min_samples_split = 5

XGBoost:

- Grid:
  - learning_rate: [0.01, 0.05, 0.1]
  - max_depth: [3, 6, 10]
  - n_estimators: [100, 300, 500]
- Final: learning_rate = 0.05, max_depth = 6, n_estimators = 300

Appendix C.4. Runtime Environment

- Programming Language: Python 3.9
- Libraries: Scikit-learn 1.1.2, XGBoost 1.6.0, Pandas 1.4.3, Numpy 1.22
- Environment: Windows 11, 64GB RAM, Intel i9, NVIDIA RTX 3080
- Random Seed: Set to 42 for reproducibility across all experiments

References

[1] Durlik, I., Miller, T., Kostecka, E., et al., 2025. Enhancing Safety in Autonomous Maritime Transportation Systems with Real-Time AI Agents. Applied Sciences. 15(9), 4986. DOI: https://doi.org/10.3390/app15094986

[2] Mohammad, A.A.S., Al Oraini, B., Mohammad, S., et al., 2024. Analysing the Relationship Between Social Content Marketing and Digital Consumer Engagement of Cosmetic Stores. In: Hannoon, A. (Ed.). Frontiers of Human Centricity in the Artificial Intelligence-Driven Society 5.0, Studies in Systems, Decision and Control. Springer Nature: Cham, Switzerland. pp. 97–109. DOI: https://doi.org/10.1007/978-3-031-73545-5_9

[3] Kim, A., Park, H.-J., Park, J.-H., et al., 2021. Rescheduling Strategy for Berth Planning in Container Terminals: An Empirical Study from Korea. Journal of Marine Science and Engineering. 9(5), 527. DOI: https://doi.org/10.3390/jmse9050527

[4] Simion, D., Postolache, F., Fleacă, B., et al., 2024. AI-Driven Predictive Maintenance in Modern Maritime Transport—Enhancing Operational Efficiency and Reliability. Applied Sciences. 14(20), 9439. DOI: https://doi.org/10.3390/app14209439

[5] Abdeljaber, O., Al-Adwan, A.S., Yaseen, H., et al., 2025. Shopping in the Metaverse: Decoding Consumer Intentions. The International Information & Library Review. 1–31. DOI: https://doi.org/10.1080/10572317.2025.2594293

[6] Aghazadeh, K., Attarnejad, R., 2024. Experimental investigation of desalination pipeline system and vapor transportation by temperature difference under sub-atmospheric pressure. Journal of Water Process Engineering. 60, 105133. DOI: https://doi.org/10.1016/j.jwpe.2024.105133

[7] Loutfy, A., Elhag, T., 2025. A Review of Determining Suitable Maintenance Strategy. CIB Conferences. 1(1). DOI: https://doi.org/10.7771/3067-4883.1961

[8] Nacchia, M., Fruggiero, F., Lambiase, A., et al., 2021. A Systematic Mapping of the Advancing Use of Machine Learning Techniques for Predictive Maintenance in the Manufacturing Sector. Applied Sciences. 11(6), 2546. DOI: https://doi.org/10.3390/app11062546

[9] Mohammad, A.A.S., Al- Daoud, K.I., Mohammad, S.I.S., et al., 2024. Analysing the Effectiveness of Omnichannel Marketing Strategies on Customer Experience in Jordan. Journal of Ecohumanism. 3(7). DOI: https://doi.org/10.62754/joe.v3i7.5063

[10] Abbas, A., 2024. AI for Predictive Maintenance in Industrial Systems. DOI: https://doi.org/10.31219/osf.io/vq8zg

[11] Patil, D., 2025. Artificial Intelligence-Driven Predictive Maintenance In Manufacturing: Enhancing Operational Efficiency, Minimizing Downtime, And Optimizing Resource Utilization. DOI: https://doi.org/10.2139/ssrn.5057406

[12] Al-Adwan, A.S., Yaseen, H., Alkhwaldi, A.F., et al., 2025. Treasure Hunting for Brands: Metaverse Marketing Gamification Effects on Purchase Intention, WOM, and Loyalty. Journal of Global Marketing. 38(4), 392–416. DOI: https://doi.org/10.1080/08911762.2025.2463897

[13] Netherton, D., 2021. Reliability-Centered Maintenance. In: Miller, B.A., Shipley, R.J., Parrington, R.J., et al. (Eds.). Analysis and Prevention of Compo-

nent and Equipment Failures. ASM International: Almere, the Netherlands. pp. 36–48. DOI: https://doi.org/10.31399/asm.hb.v11A.a0006817

[14] Elmobayed, M.G., Al-Hattami, H.M., Al-Hakimi, M.A., et al., 2024. Effect of marketing literacy on the success of entrepreneurial projects. Arab Gulf Journal of Scientific Research. 42(4), 1590–1608. DOI: https://doi.org/10.1108/AGJSR-06-2023-0266

[15] Klein, J.H., 1993. Modelling Risk Trade-Off. Journal of the Operational Research Society. 44(5), 445–460. DOI: https://doi.org/10.1057/jors.1993.81

[16] Lim, S., Oh, J., Park, J., 2025. Maintenance Time Prediction for Predictive Maintenance of Ship Engines. Applied Sciences. 15(9), 4764. DOI: https://doi.org/10.3390/app15094764

[17] Teymourian, K., Seneviratne, D., Galar, D., et al., 2019. Integrating Ergonomics in Maintanability:A Case Study from Manufacturing Industry. Journal of Industrial Engineering and Management Science. 2018(1), 131–150. DOI: https://doi.org/10.13052/jiems2446-1822.2018.008

[18] Mohammad, A.A.S., Masadeh, M., Al Sarayreh, A., et al., 2024. The Impact of the Green Supply Chain Management Practices on the Social Performance of Pharmaceutical Industries. In: Hannoon, A. (Ed.). Frontiers of Human Centricity in the Artificial Intelligence-Driven Society 5.0, Studies in Systems, Decision and Control. Springer Nature: Cham, Switzerland. pp. 325–339. DOI: https://doi.org/10.1007/978-3-031-73545-5_28

[19] Van Dinter, R., Tekinerdogan, B., Catal, C., 2022. Predictive maintenance using digital twins: A systematic literature review. Information and Software Technology. 151, 107008. DOI: https://doi.org/10.1016/j.infsof.2022.107008

[20] Balhareth, H., Al-Adwan, A.S., Alsoud, A.R., et al., 2024. Journey into meta-commerce: unveiling the driving forces of consumer adoption. Global Knowledge, Memory and Communication. DOI: https://doi.org/10.1108/GKMC-05-2024-0307

[21] Budimir, D., Medić, D., Ružić, V., et al., 2025. Integrated Approach to Marine Engine Maintenance Optimization: Weibull Analysis, Markov Chains, and DEA Model. Journal of Marine Science and Engineering. 13(4), 798. DOI: https://doi.org/10.3390/jmse13040798

[22] Sarode, G.C., Gholap, P., Pathak, K.R., et al., 2025. Edge AI and Explainable Models for Real-Time Decision-Making in Ocean Renewable Energy Systems. Sustainable Marine Structures. 7(3). DOI: https://doi.org/10.36956/sms.v7i3.2239

[23] Mohammad, A.A.S., Alshebel, M., Al Oraini, B., et al., 2024. Research on Multimodal College English Teaching Model Based on Genetic Algorithm. Data and Metadata. 3, 421. DOI: https://doi.org/10.56294/dm2024421

[24] Shamim, M.M.R., Ruddro, R.A., 2025. Smart Diagnostics in Industrial Maintenance: A Systematic Review of Ai-Enabled Predictive Maintenance Tools and Condition Monitoring Techniques. ASRC Procedia: Global Perspectives in Science and Scholarship. 01(01), 63–80. DOI: https://doi.org/10.63125/b4tn2x46

[25] Agarwal, V., Sabir, M., Mishra, S., et al., 2024. Predictive Maintenance Unleashing Applications of Machine Learning: A Comprehensive Exploration. International Journal of Technical Research & Science. 9(Spl), 27–35. DOI: https://doi.org/10.30780/specialissue-ISET-2024/009

[26] Bunyan, S.T., Khan, Z.H., Al-Haddad, L.A., et al., 2025. Intelligent Thermal Condition Monitoring for Predictive Maintenance of Gas Turbines Using Machine Learning. Machines. 13(5), 401. DOI: https://doi.org/10.3390/machines13050401

[27] Aghazadeh, K., Attarnejad, R., 2020. Study of sweetened seawater transportation by temperature difference. Heliyon. 6(3), e03573. DOI: https://doi.org/10.1016/j.heliyon.2020.e03573

[28] Maiorano, C., Pascale, E., Schenkelberg, F., et al., 2019. MTBF (Metric That Betrays Folk). In Proceedings of the 29th European Safety and Reliability Conference (ESREL), Hannover, Germany, 22–26 September 2019; pp. 2454–2460. DOI: https://doi.org/10.3850/978-981-11-2724-3_0963-cd

[29] Maataoui, S., Bencheikh, G., Bencheikh, G., 2023. Predictive Maintenance in the Industrial Sector: A CRISP-DM Approach for Developing Accurate Machine Failure Prediction Models. In Proceedings of the 2023 Fifth International Conference on Advances in Computational Tools for Engineering Applications (ACTEA), Zouk Mosbeh, Lebanon, 5 July 2023; pp. 223–227. DOI: https://doi.org/10.1109/ACTEA58025.2023.10193983

[30] Koković, V., Pavlović, K., Mijanović, A., et al., 2024. Exploring statistical and machine learning methods for modeling probability distribution parameters in downtime length analysis: a paper manufacturing machine case study. Journal of Big Data. 11(1), 162. DOI: https://doi.org/10.1186/s40537-024-01030-4

[31] Alaswad, S., Xiang, Y., 2017. A review on condition-based maintenance optimization models for stochastically deteriorating system. Reliability Engineering & System Safety. 157, 54–63. DOI: https://doi.org/10.1016/j.ress.2016.08.009

[32] Chelliah, B.J., Gahra, S.K., Senthilselvi, A., et al., 2024. Smart Ports: Utilizing AI-Driven Predictive Analytics and Simulation for Operational Excellence. In Proceedings of the 2024 International Conference on Smart Technologies for Sustainable

Development Goals (ICSTSDG), Chennai, India, 6 November 2024; pp. 1–7. DOI: https://doi.org/10.1109/ICSTSDG61998.2024.11026747

[33] Riaventin, V.N., Tri, R., Suprayogi, C., et al., 2023. Towards Integration of Truck Appointment System and Direction for Future Research. In Proceedings of the 3rd Asia Pacific Conference on Industrial Engineering and Operations Management in Jahor Baru, Malaysia, Jahor Baru, Malaysia, 13 September 2022. pp. 3022–3030. DOI: https://doi.org/10.46254/AP03.20220509

[34] Saydam, D., Frangopol, D.M., 2015. Risk-Based Maintenance Optimization of Deteriorating Bridges. Journal of Structural Engineering. 141(4), 04014120. DOI: https://doi.org/10.1061/(ASCE)ST.1943-541X.0001038

[35] Selvik, J.T., Aven, T., 2011. A framework for reliability and risk centered maintenance. Reliability Engineering & System Safety. 96(2), 324–331. DOI: https://doi.org/10.1016/j.ress.2010.08.001

[36] Al-Madadha, A., Al-Adwan, A.S., Falahat, M., 2025. How emotional intelligence and spiritual intelligence foster employee engagement and organizational success. Journal of Modelling in Management. DOI: https://doi.org/10.1108/JM2-02-2025-0064

[37] Jahani, S., Zhou, S., Veeramani, D., 2021. Stochastic prognostics under multiple time-varying environmental factors. Reliability Engineering & System Safety. 215, 107877. DOI: https://doi.org/10.1016/j.ress.2021.107877

[38] Thielmann, M., 2021. The analysis of the impact of environmental factors on turbine performance, develpoment of the models relating the periods between maintenances with selected maintenance factors. Inżynieria Bezpieczeństwa Obiektów Antropogenicznych. (3), 1–10. DOI: https://doi.org/10.37105/iboa.113

[39] Ohoriemu, O.B., Ogala, J.O., 2024. Integrating Artificial Intelligence and Mathematical Models for Predictive Maintenance in Industrial Systems. FUDMA JOURNAL OF SCIENCES. 8(3), 501–505. DOI: https://doi.org/10.33003/fjs-2024-0803-2593

[40] Mohammad, A.A.S., Al- Daoud, K.I., Al Oraini, B., et al., 2024. Using Digital Twin Technology to Conduct Dynamic Simulation of Industry-Education Integration. Data and Metadata. 3, 422. DOI: https://doi.org/10.56294/dm2024422

[41] Gomaa, A.H., 2025. RCM 4.0: A Novel Digital Framework for Reliability-Centered Maintenance in Smart Industrial Systems. International Journal of Emerging Science and Engineering. 13(5), 32–43. DOI: https://doi.org/10.35940/ijese.E2595.13050425

[42] Ibazebo, E., Savsani, V., Siddhpura, A., et al., 2025. Novel Fuzzy Multi-Criteria Decision Framework for Maritime Infrastructure Maintenance. Infrastructures. 10(4), 89. DOI: https://doi.org/10.3390/infrastructures10040089

[43] Sepehri, A., Kirichek, A., Van Den Heuvel, M., et al., 2024. Smart, sustainable, and circular port maintenance: A comprehensive framework and multi-stakeholder approach. Journal of Environmental Management. 370, 122625. DOI: https://doi.org/10.1016/j.jenvman.2024.122625

[44] Hujran, O., Al-Debei, M.M., Al-Adwan, A.S., et al., 2023. Examining the antecedents and outcomes of smart government usage: An integrated model. Government Information Quarterly. 40(1), 101783. DOI: https://doi.org/10.1016/j.giq.2022.101783

[45] S. Prabu, R. Senthilraja, Ahmed Mudassar Ali, et al., 2025. AI-Driven Predictive Maintenance for Smart Manufacturing Systems Using Digital Twin Technology. International Journal of Computational and Experimental Science and Engineering. 11(1). DOI: https://doi.org/10.22399/ijcesen.1099

[46] Shokare, C., 2025. Enhancing Decision Support Systems with Hybrid Machine Learning and Operations Research Models. Asian Journal of Science, Technology, Engineering, and Art. 3(2), 240–253. DOI: https://doi.org/10.58578/ajstea.v3i2.4933

[47] Scaife, A.D., 2024. Improve predictive maintenance through the application of artificial intelligence: A systematic review. Results in Engineering. 21, 101645. DOI: https://doi.org/10.1016/j.rineng.2023.101645

[48] Henneberry, D., Ziakkas, D., Doerrstein, F., 2025. The role of Artificial Intelligence (AI) applications in Aviation Risk Management. In Proceedings of the 13th International Conference on Human Interaction & Emerging Technologies: Artificial Intelligence & Future Applications, Costa Del Sol, Spain, 22–24 April 2025. DOI: https://doi.org/10.54941/ahfe1005892

[49] Ajayi, O., 2025. Leveraging Artificial Intelligence for Predictive Maintenance in Logistics Infrastructure: A Framework for Enhanced Operational Efficiency. International Journal of Advances in Engineering and Management. 7(3), 623–629. DOI: https://doi.org/10.35629/5252-0703623629

[50] Gu, B., Liu, J., 2023. Port resilience analysis based on the HHM-FCM approach under COVID-19. Ocean & Coastal Management. 243, 106741. DOI: https://doi.org/10.1016/j.ocecoaman.2023.106741

[51] Yaseen, H., Al-Adwan, A.S., Nofal, M., et al., 2023. Factors Influencing Cloud Computing Adoption Among SMEs: The Jordanian Context. Information Development. 39(2), 317–332. DOI: https://doi.or

g/10.1177/02666669211047916

[52] Görür, O.C., Yu, X., Sivrikaya, F., 2021. Integrating Predictive Maintenance in Adaptive Process Scheduling for a Safe and Efficient Industrial Process. DOI: https://doi.org/10.20944/preprints202105.0040.v1

[53] Adeoye Taofik Aderamo, Henry Chukwuemeka Olisakwe, Yetunde Adenike Adebayo, et al., 2024. AI-enabled predictive safeguards for offshore oil facilities: Enhancing safety and operational efficiency. Comprehensive Research and Reviews in Engineering and Technology. 2(1), 023–043. DOI: https://doi.org/10.57219/crret.2024.2.1.0060

[54] Al-Adwan, A.S., 2024. The meta-commerce paradox: exploring consumer non-adoption intentions. Online Information Review. 48(6), 1270–1289. DOI: https://doi.org/10.1108/OIR-01-2024-0017

[55] Naeeni, S.T.O., Firozjaei, M.R., Hajebi, Z., et al., 2023. Investigation of the performance of the response surface method to optimize the simulations of hydraulic phenomena. Innovative Infrastructure Solutions. 8(1), 10. DOI: https://doi.org/10.1007/s41062-022-00977-8

[56] Pham, T.Y., 2023. A smart port development: Systematic literature and bibliometric analysis. The Asian Journal of Shipping and Logistics. 39(3), 57–62. DOI: https://doi.org/10.1016/j.ajsl.2023.06.005