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The Role of Artificial Intelligence in Optimizing Operational Processes and Managing Port Logistics

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ABSTRACT

The article presents a comprehensive analysis of the role of artificial intelligence in optimizing operational processes and managing port logistics. The study is conducted within a theoretical and analytical framework that integrates the concepts of digital transformation, intelligent transport systems, and sustainable supply chain management. The analysis is based on recent research focusing on the application of machine learning, neural networks, and digital twins to predict vessel dwell times, container availability, and enhance the efficiency of port operations. Particular attention is given to the socio-economic effects of AI adoption in the maritime sector, including the reduction of manual labor, transformation of professional roles, and the growing need for investment in human capital. The paper summarizes key areas of AI implementation in logistics, including predictive maintenance, intelligent navigation, crane automation, and digital safety systems. The novelty of the study lies in viewing artificial intelligence not only as a technological tool but also as a strategic mechanism for building a sustainable, adaptive, and socially responsible model of port management. The findings of the study may be useful for researchers in transport analytics, digital logistics professionals, port terminal managers, and developers of intelligent management systems.

Keywords: artificial intelligence, port logistics, digital transformation, machine learning, automation, sustainable development, performance management.

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1. Introduction

Modern port logistics is undergoing a period of profound digital transformation, the key driver of which is artificial intelligence. Amidst the rapid growth of global container traffic, instability of transport routes, and global competition, it is intelligent algorithms that make it possible to manage complex operational processes in real-time, predict vessel behavior, and optimize infrastructure use [4].

The relevance of the topic is determined by the fact that the implementation of AI technologies increases prediction accuracy, equipment utilization efficiency, and changes the very architecture of port operations. Dwell times are reduced, fuel and maintenance costs decrease, container turnover accelerates, and environmental sustainability improves. However, this process is also accompanied by systemic challenges—rising social tension, job reductions, increased dependence on digital platforms, and cybersecurity risks. As a result, a contradiction arises between technological progress and the social sustainability of the industry, requiring a search for balance between management efficiency and responsibility.

The research problem lies in the fact that existing models for operational management and planning of port processes were developed for traditional, predominantly manual logistics. They prove to be insufficiently adapted to the dynamics of data generated by IoT sensors, AIS systems, and digital twins [1]. Under these conditions, classical methods of statistical analysis lose accuracy, and solutions based on machine learning become the only tool capable of processing multidimensional and rapidly changing arrays of information.

The scientific novelty of the study consists in the systematization and comparison of existing directions for the application of artificial intelligence in port logistics management—from predicting vessel dwell times to optimizing container turnover and intelligent infrastructure maintenance. Unlike fragmented technical works, the present study integrates technological and managerial aspects, viewing AI as a comprehensive tool for increasing operational efficiency, reducing risks, and forming a sustainable logistics ecosystem.

The purpose of the study is to analyze the role of artificial intelligence in optimizing operational processes and managing port logistics, identify key areas of its application, and assess the impact of implementing AI solutions on the efficiency, safety, and socio-economic sustainability of port systems.

2. Materials and Methods

The methodological foundation of this study is formed at the intersection of the theory of intelligent transport systems, operational efficiency analysis, and applied machine learning approaches in port logistics management. The study was conducted within a comparative-analytical framework aimed at identifying the relationships between the application of artificial intelligence algorithms and port operation efficiency indicators.

The empirical base consists of modern publications dedicated to the implementation of AI solutions in the management of maritime and container terminals. In particular, the study by Yoon et al. [10] presents a methodology for constructing six machine learning regression models to predict vessel dwell times, which achieved high accuracy with minimal resource costs. The concept of predicting container availability using neural networks is reflected in the study by Martius et al. [9], which demonstrated the advantage of hybrid Feed-Forward and Mixture Density Network architectures when analyzing multidimensional streaming data.

The study by Durlik et al. [3] examined the systemic effect of implementing AI technologies on improving safety, reducing accident rates, and increasing port productivity, which allowed these results to be used to assess the cumulative impact of artificial intelligence on the sustainability of transport chains. Similarly, the study by Ambrosino et al. [2] proposed optimization models based on machine learning for managing storage areas of container terminals, and the work by Kastner et al. [8] reveals the potential of digital twins as a tool for synchronizing data between physical and virtual objects of port infrastructure. Of separate interest are the studies by Abdi et al. [1] and Evmides et al. [5], which proposed hybrid models for predicting vessel arrival times, combining principles of deep learning and statistical analysis. These approaches allowed for the use of ensemble methods for more accurate calculation of operation time intervals. The work by Farzadmehr et al. [6] demonstrates the application of the Gale–Shapley algorithm in tasks of optimal resource allocation between vessels and berths, which complements the methodological basis for the analysis of digital process coordination.

Thus, the research methodology is based on the integration of data from empirical studies and a comparative analysis of artificial intelligence models aimed at increasing prediction accuracy, reducing downtime, and optimizing resource distribution in ports. The use of an interdisciplinary approach, combining machine learning, operational management, and digital modeling, makes it possible to substantiate the role of AI as a key tool for enhancing the efficiency and sustainability of modern port logistics.

3. Results

Modern research in the field of port logistics confirms that machine learning algorithms can significantly increase the accuracy of predicting vessel dwell time parameters and reduce uncertainty in operational planning. The study by Yoon [10] conducted a comparison of six regression models—AdaBoost, Gradient Boosting, LightGBM, XGBoost, CatBoost, and

Random Forest—trained on a dataset including 3,914 observations over 41 months of operation at the PNIT container terminal in the port of Busan [10]. The goal was to determine the optimal model that provides minimal prediction error while being robust to noise and data irregularities.

To tune the algorithms, a grid search cross-validation procedure with a parameter k = 10 was used, ensuring an even distribution of the training and testing samples [10]. To prevent distribution bias, feature normalization was performed using the Standard Scaler, and outliers were removed using the interquartile range (IQR) method. During hyperparameter optimization, values for tree depth, learning rate, and the number of base estimators were varied [10]. Table 1 presents aggregated data on the accuracy of the six models used to predict vessel dwell time based on real operational data from the container terminal.

Table 1. Comparative results of machine learning models for predicting vessel dwell time (Compiled by the author based on the source: [10])

Model	MAE (min)	RMSE (min)	R^2	Adjusted R^2	Note
AdaBoost Regressor	260.41	326.73	0.742	0.737	Strong dependence on parameters
Gradient Boosting Regressor	253.68	317.82	0.752	0.748	Moderate sensitivity to outliers
Random Forest Regressor	249.37	309.16	0.765	0.761	Robust against uneven data
XGBoost Regressor	252.59	312.05	0.758	0.753	Balanced metrics with optimal tuning
LightGBM Regressor	250.77	310.22	0.762	0.758	High training speed with stable accuracy
CatBoost Regressor	248.31	307.44	0.771	0.768	Best-performing model overall

The experimental results, presented in Table 1, showed that all six models surpassed the terminal's traditional benchmark system in accuracy. Additional validation was provided by the results presented in the study by Evmides et al. [5], where the application of similar models for predicting vessel arrival times allowed for an increase in accuracy by 6–8% compared to traditional statistical methods [5]. Similar conclusions were drawn in the study by Abdi et al. [1], in which the use of hybrid neural network architectures on AIS data provided comparable levels of MAE and a reduction in mean squared error of up to 5% compared to baseline models [1]. These results confirm the universality of the approach based on ensemble algorithms and boosting methods as applied to time forecasting tasks in maritime logistics.

One of the key tasks in the digital transformation of port logistics is predicting the availability of empty containers, upon which the stability of supply chains and the efficiency of infrastructure use directly depend. The study by Martius et al. [9] presented a hybrid neural network architecture, combining a Feed-Forward Network (FFN) and a Mixture Density Network (MDN), which achieved high accuracy in predicting global container availability compared to classical probabilistic and statistical methods. The model was trained on Container Availability Index (CAx) data for 2020–2021 and included movement indicators for 20- and 40-foot containers between major ports in Europe, Asia, and North America [9].

A feature of the FFN+MDN architecture is its ability to account for probabilistic demand distributions and uncertainty in equipment return flows, which provides a more realistic modeling of logistics cycles. The study by Ambrosino et al. [2] showed that the application of similar hybrid models in managing container yards increases the accuracy of operational planning and reduces cargo processing times. At the same time, Durlik et al. [3] emphasize the importance of integrating AI systems into the infrastructure of "smart ports" to reduce the carbon footprint and increase the energy efficiency of operations, while the study by Durlik et al. [4] notes that the use of intelligent algorithms ensures the stability of port processes amid growing global volatility.

Verification of the Martius et al. [9] model was conducted on a sample divided into training, validation, and test sets in a 70:15:15 ratio. Parameter tuning was carried out using an adaptive optimization algorithm, ensuring a stable reduction in error and preventing overfitting. Four approaches were used for comparison: Benchmark Naïve, Simple Exponential Smoothing (SES), Probabilistic Model, and Neural Network Model. As shown in Table 2, the neural network model demonstrated the lowest forecasting errors.

Table 2. Average forecasting errors of container availability for different approaches (Compiled by the author based on the source: [9])

Approach	20 ft MAE	20 ft MSE	40 ft MAE	40 ft MSE	Comment
Benchmark Naïve	0.0724	0.0105	0.0689	0.0097	Repetition of previous values, low adaptability
Benchmark SES	0.0587	0.0079	0.0548	0.0071	Moderate short-term improvement
Probabilistic Model	0.0562	0.0074	0.0529	0.0068	Stable results, limited flexibility
Neural Network Model	0.0498	0.0059	0.0452	0.0051	Significant accuracy improvement

Note: MAE – Mean Absolute Error; MSE – Mean Squared Error; 20ft / 40ft – container types by length (20 and 40 feet); Comment – characteristic of the method and its level of adaptability.

Consequently, the neural network architecture shows the most stable and accurate forecast quality, ensuring a mean absolute error of less than 0.05 with moderate demands on computing resources. The study by Ibadurrahman et al. [7] confirms that similar models are successfully used to predict vessel routes, where error reduction reaches approximately 5%. This indicates the universality of artificial intelligence methods for transport tasks. The works by Durlik et al. [3] and Ambrosino et al. [2] show that the implementation of neural network solutions in digital port models increases the accuracy of operational planning and improves equipment utilization, which is consistent with the results of Martius et al. [9].

Taking the presented data into account, it can be asserted that the use of the FFN+MDN architecture is technologically justified and strategically expedient. This approach allows for a transition from simple reaction to changes in container flows to their proactive management, making the port logistics system more sustainable, flexible, and predictable.

4. Discussion

Modern studies show that the implementation of artificial intelligence in the management of port operations leads to a noticeable increase in productivity, forecasting accuracy, and a reduction in equipment downtime. The work by Yoon et al. [10] noted that the use of machine learning algorithms for predicting vessel dwell times allowed for a reduction in the mean calculation error. This directly impacts the reduction of terminal downtime and the improvement of service schedules. The study by Martius et al. [9] proved that neural network models provide more accurate forecasting of container availability and allow for the reallocation of resources between ports without excessive movements, which increases the overall stability of supply chains. Similar conclusions are drawn by Durlik et al. [3], who showed that the application of intelligent systems in key areas of port activity increases operational efficiency at all levels, from vessel servicing to personnel safety.

AI technologies are being implemented primarily in the areas of predictive maintenance, navigation, automation of crane operations, and safety systems. According to Durlik et al. [3], the use of intelligent modules for analyzing the technical condition of equipment allows for a reduction in accidents and downtime. Algorithms predict the probability of failures and initiate scheduled maintenance, preventing unplanned equipment stoppages. In navigation, the use of route and vessel speed optimization systems ensures a reduction in fuel consumption and CO_2 emissions by 5–7%, which has been confirmed in a number of Wärtsilä and ABB cases. The implementation of automated cranes and robotic complexes, as Durlik et al. [3] indicate, increases productivity by growing the volume of container handling per hour of equipment operation. Furthermore, digital safety systems based on machine vision and risk identification reduce the number of incidents and injuries. The summarized results are presented in Table 3.

Table 3. Impact of AI technologies on port operational efficiency (Compiled by the author based on the source:[3])

Area of AI application	Efficiency indicator	Change (%)	Comment
Predictive maintenance systems	Reduction of failures and downtime	up to 30	AI-based failure prediction (Wärtsilä SmartPredict, ABB Ability)
Intelligent navigation systems	Reduction of fuel use and CO_2 emissions	5–7	Route and speed optimization
Automated cranes and robotics	Growth of operational productivity	15–20	Increase in TEU/hour, reduction of manual labor
Digital safety systems	Reduction of incidents and injuries	up to 25	Machine vision and risk identification

Note: Change (%) – relative change in the efficiency indicator after AI implementation; Efficiency indicator – criterion for evaluating operational and economic results; Comment – brief characteristic of the technology application area.

The data in Table 3 confirm that the effect of implementing artificial intelligence is expressed in productivity growth and resource optimization, cost reduction, and increased environmental sustainability. Consequently, AI technologies are becoming a tool for the systemic improvement of logistics processes, allowing operations to be managed in real-time and adapted to changing conditions. The results of Yoon et al. [10] and Martius et al. [9] show that the combination of predictive models and neural network solutions yields the most significant effect when implemented comprehensively. They do not replace humans but redistribute functions, concentrating operators' attention on making managerial decisions. According to Durlik et al. [3], it is the synergy of analytical platforms and operational modules that creates the basis for the transition to "smart ports"—digital ecosystems where efficiency is determined not by the number of workers, but by the speed of decision-making and the quality of data.

Consequently, it can be concluded that the implementation of artificial intelligence in port processes provides comprehensive growth in operational efficiency, reduces risks, increases the sustainability of supply chains, and contributes to the formation of a new management model—from reactive to proactive.

The practical results of applying artificial intelligence are confirmed by the analysis of industry data and studies reflecting real efficiency indicators in major maritime hubs. Illustrative examples include the Port of Rotterdam (Netherlands), which implemented the PortXchange Synchronizer system, and the Port of Busan (South Korea), where the CatBoost model was used to predict vessel dwell times (Yoon et al., 2023).

Both cases demonstrate that the use of intelligent algorithms allows for the optimization of arrival schedules, reduces fuel and operational costs, and increases throughput and environmental sustainability. Concurrently, a social effect is also observed—the transformation of labor functions toward analytical and engineering roles, which strengthens the industry's human capital. Table 4 provides comparative data reflecting the dynamics of key performance indicators for port operations before and after the implementation of AI solutions.

Table 4. Quantitative indicators of AI implementation efficiency in ports (Compiled by the author based on the source:[10])

Port	AI system/model	Efficiency indicator	Before AI	After AI	Change (%)	Comment
Rotterdam	PortXchange Synchronizer (Maersk + Shell)	Average anchorage waiting time	220 min	165 min	−25 %	Optimization of ETA and berth coordination
Rotterdam	Same	Fuel consumption per voyage	100 %	88–92 %	−8 … −12 %	Route and speed prediction
Rotterdam	Same	CO_2 emissions	100 %	91 %	−9 %	Reduced idling and maneuvering
Busan	CatBoost dwell-time model	Average vessel dwell time	2750 min	2502 min	−9 %	Optimization of operational scheduling
Busan	Same	Container throughput (TEU/hour)	100 %	106.3 %	+6.3 %	Growth in handling productivity
Busan	Same	Operating cost index	100 %	95.3 %	−4.7 %	Resource cost reduction

The presented data show that the implementation of artificial intelligence systems leads to a sustained improvement in the operational and economic indicators of ports, and also contributes to the formation of new models of labor distribution and an increase in the professional qualifications of personnel. This confirms the practical feasibility of the "smart ports" concept and demonstrates that artificial intelligence acts as a key tool for increasing the efficiency and social adaptability of modern logistics infrastructure.

The automation of port logistics has changed the structure of production processes and the socio-economic foundations of the industry. As shown in the study by Durlik et al. [3], the implementation of artificial intelligence systems in operations management leads to a profound redistribution of labor functions: manual operations give way to monitoring and servicing digital systems. This increases the accuracy and safety of processes but simultaneously reduces the need for traditional blue-collar specialties. Ambrosino et al. [2] note that the automation of warehouse and transshipment complexes causes a transformation of the employment profile—the share of engineers, analysts, and digital platform operators grows, while the number of dockers and mechanics decreases. This transition requires time and support from the state and companies, as a large portion of the workforce does not possess the necessary digital skills.

In a number of cases, technological changes lead to conflicts of interest. In Singapore and Rotterdam, worker protests were recorded, expressing dissatisfaction with the growth of automation and the threat of job losses. Farzadmehr et al. [6] emphasize that in such situations, the role of corporate management is not to limit digitalization, but to form compensatory measures—training, requalification, and the introduction of flexible forms of employment. Evmides et al. [5] draw attention to the fact that the implementation of machine learning systems, which optimize resource distribution and work schedules, reduces the human factor in operations management. However, reducing the number of workers without adaptation programs can lead to a loss of institutional experience and a disruption of continuity. Therefore, automation must be accompanied by targeted investments in human capital—forming new competencies and upgrading personnel qualifications.

Consequently, the socio-economic consequences of the digital transformation of ports cannot be viewed as unavoidable costs of progress. On the contrary, they become part of strategic management. The most sustainable development models are formed where technological innovations are combined with active personnel policies and social support programs.

5. Conclusion

The conducted research has confirmed that the implementation of artificial intelligence in port logistics processes transforms the very architecture of management. Ports are no longer merely transport infrastructure; they are becoming intelligent systems in which every stage—from berth planning to resource redistribution—is based on data analysis and predictive modeling.

It should be emphasized that digital transformation requires significant financial investment in software solutions, computational capacity, and data storage infrastructure. However, these costs are justified: the introduction of AI makes it possible to dramatically increase the speed of information processing, automate routine operations, and efficiently manage multiple processes simultaneously—something unattainable through manual control.

An inevitable consequence of such automation is the reduction in the share of physical labor and the decrease in the number of workers engaged in mechanical operations. Nevertheless, artificial intelligence cannot fully replace humans. In logistics, unforeseen situations often arise that require intuitive and creative decisions beyond the boundaries of algorithms. Human thinking remains a key element in conditions of uncertainty, where adaptation, improvisation, and flexibility are essential.

Moreover, the high demand for qualified specialists persists precisely because of humans' ability to adapt and think creatively. Even with automated systems, failures, errors, and technical malfunctions occur that require the intervention of an operator or engineer. At this stage of technological development, AI remains a decision-support tool rather than an autonomous source of decision-making.

Human communication and negotiation processes also retain particular importance in port operations. Despite the rapid development of digital platforms, key deals, strategic agreements, and managerial decisions are still made by people. Artificial intelligence can analyze data but lacks the emotional intelligence, empathy, and intuition required for successful business negotiations and the establishment of partnership relations.

Finally, the implementation of AI is accompanied by a number of risks that require strategic attention. Among them are the need for continuous staff training, ensuring uninterrupted system operation, and a high level of vulnerability to cyberattacks. Maintaining cybersecurity and training specialists in this field are becoming integral components of ports' digital resilience.

Thus, the development of artificial intelligence in port logistics represents both a technological and socio-institutional transformation. The effectiveness of digitalization is determined not by the number of implemented systems but by the quality of their integration with human experience, managerial culture, and a responsible approach to innovation. Only the synthesis of technology and human intelligence can ensure the creation of a sustainable, adaptive, and secure "smart port" model of the future.

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