# A Recent Review on Artificial Intelligence in Ports

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Ports are investing significantly in artificial intelligence (AI). However, research remains nascent and fragmented in this area, making it complex to develop integrated plans that leverage on data. This paper presents a systematic literature review of 28 recent publications that examine the value of AI in port's digital and green transformation. The work was conducted within the scope of a multiyear investment project on the transformation of ports and logistics. The taxonomy of publications outlines the main pillars of AI application in ports: operation efficiency, support and maintenance, scheduling and forecasting capacity, environmental policies, and surveillance and human safety. Our study reveals an increase in the scale of AI adoption, including the orchestration of seaport-dry operations, multimodal transportation integration, and analysis of environmental impacts. Our contribution includes near-term use cases and guidelines to address the challenges of AI adoption in mission-critical, large-scale logistics infrastructures while promoting sustainablility.

**DOI**
https://doi.org/10.18690/um.fov.4.2026.52

**ISBN**
978-961-299-152-4

**Keywords:**
artificial intelligence,
dry port,
machine learning,
seaport,
smart port,
sustainability

University of Maribor Press

## 1 Introduction

Ports are the backbone of advanced logistics networks that support over 80% of the world's trade (Evmides et al., 2024; H. Xie & Ambrosino, 2025). On the one hand, seaports play a strategic role in establishing maritime transportation routes, which are increasingly constrained by demand for energy, valuable resources, and products that support economic development. On the other hand, dry ports, located inland and served primarily by trucks and trains, offer an effective means of reducing seaport congestion, improving container handling and storage efficiency, and contributing to local economies (Rekabi et al., 2025). Despite differences in location, size, or cargo type, all share common priorities: digital transformation, green practices, and sustainable management (Aerts & Mathys, 2024).

The term "smart port" has recently been used to describe the disruptive transformations enabled by digital technologies in these critical infrastructures for international trade (Li et al., 2023). Similar to other industry sectors, artificial intelligence (AI) is driving interest in digitalization of ports (Liu & Yuen, 2025). Grounded on the work of Russell & Norvig (1995), we define AI as the set of computational techniques (e.g., computer vision, machine learning, natural language processing) that capacitate systems to perform actions that typically require human intelligence (e.g., learning, decision-making, forecasting). The AI transition raises data governance challenges, including data quality and ownership management of shared data assets (Abraham et al., 2019). Moreover, complex platform ecosystems are necessary to coordinate the several stakeholders, enable data exchange, and foster integration (Hein et al., 2020). Lastly, AI-based solutions are delegating decision-making to automatic algorithms (Guo et al., 2025), requiring adjustments in port's organizational structures.

Relevant ports in Hamburg, Singapore, Valencia, or Rotterdam are leading the way in terms of AI adoption (Osundiran & Makgopa, 2025). Yet, "*there remains a gap, especially concerning the recent AI developments and their integration into port operations post-2022*" (Liu & Yuen, 2025). The work of Liu & Yuen (2025) is one of the most recent and comprehensive reviews of AI application in ports, detailing findings up to 2023. Our search revealed a major increase in publications in the past two years, motivating the team to extend prior research. Our Research Question (RQ) is: "*What are the emerging use cases of AI-based applications (post-2024) in port operations' Digital Transformation*

*(DT), and how do they contribute to operational and sustainable improvements?*" We frame our research through the DT process described by Vial (2019), aiming to understand how AI-based applications reshaped port's operations, contributing to automate operations, foster inter-organizational collaboration, and promote sustainable practices.

This research falls within the scope of the NEXUS – Innovation Agenda for Digital and Green Transition, a multiyear research and development project aimed at performing the digital and green transformation of ports and logistics in Portugal (NEXUS, 2026). Led by the Port of Sines and comprising 35 partners (e.g., universities, logistical operators, technology producers), NEXUS is developing an ecosystem of 28 innovative products, many of which are enabled by artificial intelligence, including federated applications and services and an open data collaboration platform. Understanding how AI is transforming ports is the main research objective of this paper, conducted in the form of a systematic literature review (Webster & Watson, 2002) of papers published since 2024, and a starting point for NEXUS intervention. Advances in AI over the past two years have created favorable conditions for summarizing knowledge on AI adoption in this essential sector of the economy, which is struggling to optimize operations and reduce environmental impacts (Rekabi et al., 2025).

The rest of this paper is structured as follows. Section 2 explains the research approach. The results of the bibliometric analysis and the systematic literature review are included in Section 3, followed by the taxonomy of recent use cases of AI adoption in ports (Section 4). The paper closes in Section 5, stating the main conclusions, limitations, and future work opportunities.

## 2 Research Approach

Our work began with a systematic literature review (SLR) using a concept-centric analysis (Webster & Watson, 2002), which was updated during the NEXUS project execution to ensure comprehensive coverage of the most relevant studies.

The current version of our sample was obtained via Scopus using the keyword combination ("artificial intelligence" OR "machine learning") AND ("smart port" OR "dry port" OR "seaport" OR "port 4.0"), yielding 210 results in the title, abstract, and keywords fields. The initial sample of 210 works was used to construct bibliometric networks to identify relevant clusters and topics using the VoS Viewer Tool (van Eck & Waltman, 2010). We removed two duplicate publications and two non-English articles, reducing the initial sample to 208 papers. We included peer-reviewed journal publications, focusing on AI adoption in ports, published since 2024 (to provide the most recent discussion of the AI literature, since it is advancing extremely fast, with almost half of the papers being published from 2024 onwards and recent reviews reporting research until 2023 (Liu & Yuen, 2025)), resulting in a sample of 43 papers. Journals or publishers that did not meet the basic threshold for national rankings were also excluded from the sample. We screened the publications' title, abstract, and keywords, resulting in a final SLR sample of 28 articles selected for full-text reading and extraction of use cases, methodologies, and results of AI adoption in ports to perform the concept-centric analysis (Webster & Watson, 2002). Figure 1 introduces the SLR schema.

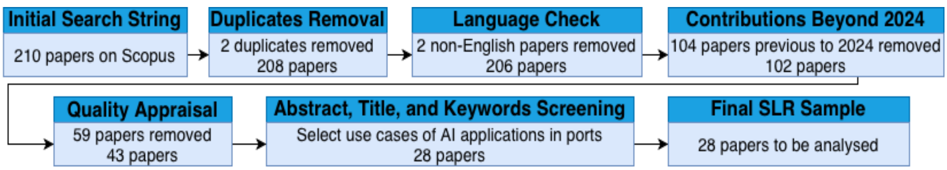


**Figure 1: SLR Procedures on AI Applications**
Source: Author's Own Work

We applied a concept-centric coding scheme, classifying studies by application domain and reported outcomes. The coding scheme was iteratively refined to align with the RQ, and ambiguous cases were reexamined to improve reliability. We iteratively reported SLR's insights during the NEXUS's project meetings, contributing to plan upcoming AI investments, anticipate implementation challenges, and forecast potential outcomes for each choice. As an example, NEXUS's deliverables included an automatic container damage identification tool and system to simulate and optimize berth allocation operations.

## 3 Results

This section details the findings for the AI-based solutions in port operations, including (1) a bibliometric analysis and (2) a SLR using a concept-centric analysis.

### 3.1 Bibliometric Analysis of Scopus Clusters

Figure 2 details the results of the bibliometric analysis for the 210 papers sample obtained in Scopus. It was a starting point to identify research priorities in the field.

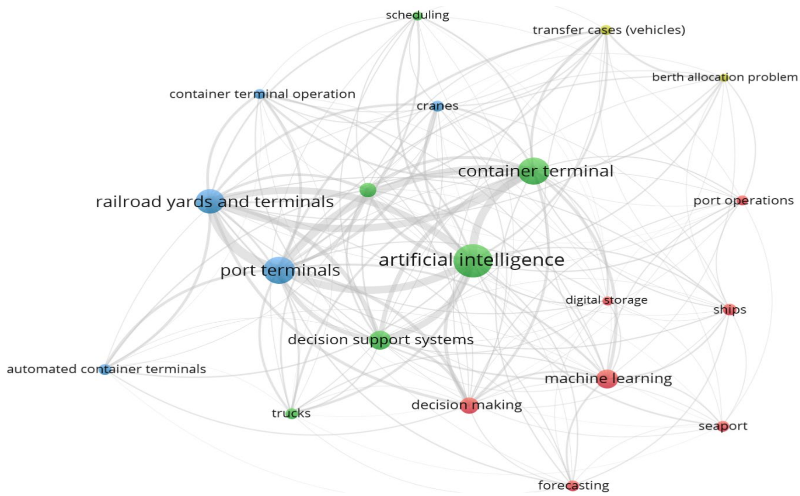


**Figure 2: Bibliometric Analysis in Scopus (keywords co-occurrence with a minimum of 15 occurrences)**
Source: Author's Own Work Using VoS Viewer

We identify four clusters in the bibliometric network in Figure 2, deploying the default VOSviewer resolution configuration to balance interpretability and granularity. The blue cluster (on the left part of Figure 2) represents port terminals and railroad yards, including automatic container terminals and corresponding operations (e.g., using cranes). The green cluster (at the center of Figure 2) highlights the role of AI in container terminal operations, addressing its deployment in decision support systems (DSSs) and scheduling. The red cluster (at the right part of Figure 2) details the use of machine learning (ML) sustained on digital storage to enable decision making and forecasting in port and ship-related operations. Lastly, the yellow cluster (at the right-top of Figure 2) focuses on the problem of berth allocation that often involves challenges related to transfer cases. The clusters reveal the multidimensional attributes of our sample, including both seaport and dry port settings, multimodal transport options, and the central role of cargo (e.g., minimizing movements) in AI models' concerns.

### 3.2 Systematic Literature Review Results

We use a concept-centric analysis to report the findings in our SLR (Webster & Watson, 2002), derived from our findings in the bibliometric clusters analysis, including AI applications for port operations. The studies included in our sample addressed relevant problems in port business. For example, (1) infrastructure management, (2) planning and scheduling, (3) traffic management, (4) environmental sustainability, (5) decision-making and forecasting in port operations, (6) asset and resource management, and (7) supply chain management. All these applications contributed to increase revenue, enhance resource and operational optimization, and promote competitiveness in the context of port operations.

In terms of infrastructure and management, we observe that machine learning (ML) algorithms operating on real-time data are increasingly used in port management, namely to overcome the limitations of rudimentary analytics. ML is used to study and predict risks of seaport disruptions induced by natural hazards (Khan et al., 2025) as well as from hazardous cargo operations (Khan et al., 2024). The recent study presented by Aslam et al. (2025) uses ML-based technology to predict faults in container handling equipment (e.g., inverters).

AI technology is applied to automate, streamline, and optimize planning and scheduling activities in the context of port operations. Berth allocation is a complex problem in port management operations, and AI is targeted as a potential enabler for more efficient and quicker solutions. In Lv et al. (2024), a deep reinforcement learning (DRL)-based model optimizes berth allocation operations. For the same problem, AI and mathematical models are applied to address complex berth allocation operations in inland water transport terminals, considering the challenges of the multiple types of handling devices, cargo, and barges (Pasha et al., 2025).

In Y. Xie et al. (2025), the researchers propose a predictive ML-based model for container out-terminal assignment that enables significant cost savings when compared with existing solutions. Also Yan et al. (2025) explore DRL algorithms to optimize container relocation operations. Another challenge that AI addresses is the quay scheduling. For example, You et al. (2025) exploit model-free DRL technology to address challenges in quay crane scheduling in terminal operations. Guo et al. (2025) develop and evaluate a novel algorithm (combining AI, flow modeling, and optimization theories) to automatically define and optimize quay and berth machinery scheduling in inland river ports. Some ports require the combination and planning of multimodal transport networks. He et al. (2025) developed and tested a novel path optimization technique to optimize multimodal transport operations.

AI is revolutionizing traffic management within the seaport and surrounding areas. Pham et al. (2024) address the challenges posed by voluminous vessel flows in seaport zones, proposing a novel integrated maritime management system that predicts traffic conditions and identifies a secure path for incoming ships, while Duan et al. (2025) propose a novel approach to address vessel traffic flow and berth allocation in high-congestion ports with varying constrained channel widths. Ports can forecast vessel arrivals and estimate their paths, improving the existing solution for predicting ship arrival times (Saber et al., 2025). Zygouras et al. (2024) develop and evaluate a method that combines ML and advanced data techniques to estimate a vessel's complete route based on its characteristics and historical information. Trucks may also cause congestion in ports. In Silva et al. (2024), the authors explore ML techniques to propose a conceptual truck appointment management system that addresses potentially impacting events by promoting the necessary flux adjustments.

Seaports face increasingly stringent regulations and ambitious emission reduction targets. In Gulyás (2025), the authors discuss how AI/ML techniques can be used to reduce the effort required to create air emission inventories (EIs) while enhancing the accuracy of these valuable monitoring instruments. Energy consumption forecasting is fundamental to optimize energy production and minimize greenhouse gas emissions. Examples of studies in this line include Song et al. (2026), who discuss the use of machine learning to forecast energy demand in modern seaports, thereby improving efficiency, reducing operating costs, and advancing carbon neutrality. Also Conte et al. (2025) use artificial intelligence techniques to forecast and optimize energy use from ships at berth, utilizing a combination of sources (e.g., shore-side electricity, multi-energy storage, renewable generation), thus mitigating their greenhouse gas emissions. Zhang et al. (2025) contribute with an energy consumption and benefit assessment model for ship operations in container terminals that contributes to estimating efficiency. AI applications can estimate and predict air quality in ports, engaging managers to develop necessary actions. AI is used to predict air quality in areas surrounding ports. In this context, Bakary et al. (2024) propose an ML-based model to estimate greenhouse gas emissions in loading and unloading operations located in quayside at seaports. Ultimately, ML, statistics, and geospatial analysis techniques are combined and applied to identify pollution hotspots in areas surrounding seaports (Cabrera-Ormaza et al., 2025).

AI can automate and augment decision-making in port operations, with a special emphasis on logistical planning. Siri et al. (2024) propose a novel Decision Support System (DSS)-based methodology to optimize train load planning in port container terminals. These new tools reveal the potential to change the role of humans in port operations, suggesting that training in more advanced DSS is necessary for operators and managers, which is not yet the norm. As AI becomes more relevant to support decision-making, human agents must be prepared to identify how to use it and the risks that may arise (e.g., poor data leading to incorrect recommendations).

AI can also be applied to the port's physical assets and resources, enabling infrastructure and equipment intelligence. Solutions target defects and faults in containers and port-related equipment. Convolutional neural networks, a subtype of ML algorithms, are used to develop a framework for automatically identifying and classifying visual defects in containers (Kuo et al., 2025). The work of Liao et al. (2024) proposes and tests an innovative approach to identify and diagnose faults in trolley mechanisms in ship-to-shore cranes, using knowledge-based reverse deep belief networks. Another possibility is to deploy AI-based systems to optimize the operationalization of port resources (e.g., cranes). In Yu et al. (2025), the authors apply computer vision techniques to estimate and monitor the swing angle of the portal crane's bucket grab, enhancing safety and security in port operations. Satellite imagery can be analyzed by AI-based algorithms to automatically estimate the number of containers in port storage infrastructures, significantly optimizing this operation while requiring fewer resources (Zhou & Wang, 2024).

AI streamlines inter-organizational collaboration with logistical chains. The combination of ML and Blockchain technology enhances security and information integration, improving traceability, logistics, and inter-organizational processes in port operations (Durán et al., 2024). For example, Rekabi et al. (2025) explore ML and IoT to create a novel dry port-seaport logistical network that assesses the impact of sustainable practices (e.g., CO2 emissions), enables real-time activity monitoring and prediction, and estimates demand forecasting and waste management.

Most of the analyzed AI-based solutions relied on near real-time, interoperable, and high-quality data collected from multiple devices and stakeholders (e.g., berth planning). The analysis of the results also highlights that most advanced AI implementations are applied in optimization operations (e.g., traffic management), while exploratory solutions target strategic planning and automation (e.g., risk assessment).

## 4 A Taxonomy of Use Cases for the NEXUS Agenda

Table 1 summarizes the findings for AI-enabled smart port implementation and their contribution to the United Nations' Sustainable Development Goals (SDGs) (United Nations, 2026), based on the insights of the SLR.

Table 1 extends the important work presented by Liu & Yuen (2025) to understand the most recent landscape of AI adoption in ports. Furthermore, it offers a practice-oriented taxonomy to deploy AI in optimizing port operations and promoting sustainability practices, focusing not only on the port itself, but also on the entire logistical chain of stakeholders. Lastly, it includes a reflection on the contribution of AI-based solutions to achieving SDGs. Our results have been iteratively updated over the past two years to ensure the adoption of state-of-the-art AI.

Our research contributes to the DT literature, demonstrating how the AI adoption is reshaping organizational capabilities by enabling automatic processes and data-driven decision making. In this context, reshaped inter-organizational data exchange networks become a priority to integrate decentralized information systems and streaming information dissemination. Consequently, digital governance structures are necessary to ensure accountability, coordination, and control in ports' multi-stakeholder setups.

The increased AI adoption requires a socio-technical transformation of organizational structures (Murire, 2024), in which technological solutions are blended with human roles and work practices to perform tasks and make decisions. Furthermore, the implementation of AI-based solutions supporting automatic decisions raises issues associated with accountability and risk (Cheong, 2024). Subsequently, ports must reorganize their organizational structures to include new roles, decision-making processes, and accountability for automated decisions.

**Table 1: AI-Enabled Smart Port: A Taxonomy of Recent Use Cases**

| Scope | Use Case | SDGs | References |
|---|---|---|---|
| Port: terminal infrastructure and management | Energy optimization and forecasting<br>Intelligent infrastructure maintenance<br>[Data] Governance, legal, and ethical assessment<br>Risk/hazards assessment and prediction<br>Emissions inventory accuracy | SDG-7<br>SDG-9<br>SDG-13<br>SDG-14 | (Aslam et al., 2025; Conte et al., 2025; Gulyás, 2025; Khan et al., 2024, 2025; Song et al., 2026; Zhang et al., 2025) |
| Port: cargo (e.g., containers) handling | Container relocation and stacking<br>Container counting<br>Berth planning<br>Vessel berthing optimization<br>Estimated time of arrival<br>Throughput under supply chain disruptions<br>Parking facility improvement<br>Load/unload planning/sequencing<br>Container location optimization | SDG-9<br>SDG-13 | (Lv et al., 2024; Pasha et al., 2025; Saber et al., 2025; Siri et al., 2024; H. Xie & Ambrosino, 2025; Yan et al., 2025; Zhou & Wang, 2024) |
| Port: gate | Container identification, damage, and defect categorization<br>Predict and/or reduce congestion | SDG-9<br>SDG-13<br>SDG-14 | (Kuo et al., 2025; Y. Xie et al., 2025) |
| Port: quay cranes | Motion detection<br>Machinery scheduling<br>Fault diagnosis | SDG-9 | (Guo et al., 2025; Liao et al., 2024; You et al., 2025; Yu et al., 2025) |
| Third party: Environmental quality | Environmental monitoring<br>Pollutants prediction | SDG-9<br>SDG-13<br>SDG-14 | (Bakary et al., 2024; Cabrera-Ormaza et al., 2025) |
| Third party: port network | Seaport – dry port cargo movements optimization<br>Port–city integration<br>Port selection | SDG-9<br>SDG-13<br>SDG-14 | (Durán et al., 2024; He et al., 2025; Rekabi et al., 2025) |
| Third party: Transportation operators | Optimize energy in transport operations<br>Truck routing optimization<br>Autonomous navigation/driving<br>Shipboard microgrids | SDG-9<br>SDG-13<br>SDG-14 | (Silva et al., 2024; Zygouras et al., 2024) |
| Third party: Authorities | Safe maritime/ship traffic control<br>Satellite-based bathymetry in seaports<br>Small non-metallic vessels detection<br>Inspections recommendations | SDG-9<br>SDG-14<br>SDG-16 | (Duan et al., 2025; Pham et al., 2024) |

Source: Author's Own Work

The deployment of AI-based solutions requires massive volumes of input data incoming from multiple infrastructures across the port (e.g., real-time data collection to predict traffic in the port (Pham et al., 2024)) and the distinct stakeholders in the logistical chain (e.g., data from vessels arriving at the port (Saber et al., 2025), optimizing multimodal transport routes (He et al., 2025)). As a consequence, ports must deploy data governance practices to manage data sharing operations, meet data quality thresholds, and secure sensitive data (Abraham et al., 2019).

The deployment of AI can foster the "smart"- "green" port nexus (Dey et al., 2025), exploiting digital technologies to promote SDGs (United Nations, 2026). Regarding SDG7 – "*Affordable and Clean Energy*", AI technologies support ports in optimizing and predicting energy consumption in infrastructures and ships. Focusing on SDG9 – "*Industry, Innovation and Infrastructure*", AI is enabling the implementation of intelligent, safer, and resilient ports. For SDG 13 – "*Climate Action*", AI is enabling ports to make operations more efficient, promote environmental awareness, and reduce resource waste. Focusing on SDG 14 – "*Life Below Water*", AI-based solutions promote sustainable maritime practices that mitigate impact on seas and biodiversity.

Despite the inspirational works found in recent years advancing AI in ports, there are also relevant gaps in the literature that we confirmed in our field interventions in the NEXUS agenda. First, there is a lack of comprehensive evaluations of the business value of AI in ports. Most studies still address the operational level of decision-making, missing the analysis of the economic or societal benefits of AI (for example, quantifying waste reduction or the potential benefits to human safety during port operations). Second, while leading ports have already included AI in their investment agenda, it is not clear how the IT companies' ecosystem is incorporating AI into their offerings (e.g., terminal operating systems) and how AI use in daily operations is uncertain. Accurate recommendations require reliable data, which is not always available in port settings, and may also require data from third-party operators. Data integration between the port and other stakeholders is challenging. Third, there is a lack of studies focusing on agentic AI. Many operations may be delegated to intelligent agents (e.g., information requests to operators), but we found no studies that highlight agentic AI use cases or provide empirical examples. Future work is needed to shift AI's impact from near-term decisions (e.g., defect classification) to strategic value and autonomy in port operations. Given the diversity of ports and their networks, large-scale projects are necessary to obtain the data and accuracy levels critical to modern logistics networks. However, we gathered positive indications from existing studies and our contacts with port practitioners that the road to more effective AI use is already being developed.

## 5 Conclusion

This article presents the results of an SLR on AI adoption in port operations. We provide insights into field interventions within the NEXUS investment project. We systematize recent (2024-2026) use cases and suggestions for AI adoption in port operations, along with existing challenges, to further advance the adoption of technological solutions in the sector and promote sustainable practices.

Some limitations must be stated. First, our analysis was based on Scopus, limiting the validity of our findings. Future research can include other bibliographical databases (e.g., Web of Science). Second, the empirical insights for the AI-enabled smart port implementation focus on recent studies, aiming to capture the trends in this field and inform one of the largest European co-funded projects of port transformations. As a consequence, works published before 2024 were not included in the review. Upcoming research stages are aimed at extending the analytical synthesis to identify cross-cutting patterns and maturity levels of AI application in ports. Future work may address the gaps found, namely (1) evidence of IA impact in port strategies, (2) network use of AI requiring data lakes and trustworthy logistical operations data in a wider scale, and (3) prioritizing agentic AI to assist humans in port operations.

**Acknowledgment**

This work was supported by Portuguese Recovery and Resilience Plan (PRR) within the scope of the Agenda "NEXUS: Pacto de Inovação–Transição Verde e Digital para Transportes, Logística e Mobilidade" (Investment Project No. 53) under Grant C645112083-00000059. This work was also developed within the scope of the research undertaken by Research Unit–Centre for Informatics and Systems of the University of Coimbra–Grant UID/00326 - Foundation for Science and Technology (FCT), I.P.

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