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AI-Driven Decarbonization Strategies for Maritime Ports: A Systematic Review with PRISMA and Bibliometric Analysis

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Abstract: The increasing pressure on maritime ports to reduce greenhouse gas emissions has accelerated the adoption of artificial intelligence to support decarbonization strategies. However, existing research remains fragmented across operational, environmental, and energy domains. This study provides a structured analysis of artificial intelligence applications in port decarbonization by integrating a systematic review with bibliometric analysis. A total of 165 records were identified from the Scopus database, and after screening and eligibility assessment, 62 peer-reviewed articles published between 2021 and 2025 were included in the final analysis. The systematic review identifies four major thematic areas: energy management, emission monitoring and prediction, operational optimization, and renewable and alternative energy integration. The bibliometric analysis complements these findings by revealing dominant research clusters and the intellectual structure of the field. The results indicate that operational optimization represents the most mature application area, delivering efficiency gains that contribute to indirect emission reduction. Emission monitoring and prediction provide accurate environmental diagnostics but remain limited in decision support integration. Energy management demonstrates growing application with varying impact on emission reduction, while renewable and alternative energy integration remains an emerging field with strong long-term potential. Despite these advances, several gaps persist, including limited real-world validation, fragmented data environments, and weak integration between predictive models and operational decision-making. The study contributes by providing an integrated perspective that links artificial intelligence techniques with port operations and decarbonization outcomes. The findings offer insights for researchers, port authorities, and policymakers seeking to advance the implementation of artificial intelligence in sustainable port development.

Keywords: Artificial intelligence; Maritime ports; Port decarbonization; Energy management; Emission monitoring; Operational optimization; Systematic review; Bibliometric analysis

1 Introduction

Maritime ports play a central role in global logistics and remain a major contributor to carbon emissions. Emissions arise from vessel activities, cargo handling, yard equipment, energy consumption, and the movement of trucks within port areas. The international maritime community continues to pursue pathways toward cleaner port operations through global and regional initiatives that encourage lower carbon output [1].

The use of intelligent optimization systems has emerged as a promising approach for addressing energy use, emission control, and operational optimization. Artificial intelligence-based models are now present in the forecasting of emissions, planning of port operations, predictive maintenance, and decision support systems. However, current research is fragmented across different areas and lacks a unified understanding of how artificial intelligence contributes to decarbonization in ports.

This study addresses this gap through a systematic review supported by Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) screening and bibliometric analysis. The bibliometric approach provides insight into conceptual structures, influential scholars, and dominant research directions. The integration of PRISMA and VOSviewer offers a comprehensive overview of how intelligent optimization systems have been applied to reduce carbon emissions in ports and highlights opportunities for further development.

Despite the increasing volume of research at the intersection of artificial intelligence, port operations, and environmental sustainability, the existing body of literature remains dispersed across multiple disciplinary domains. Previous studies have typically examined port digitalization, operational optimization, or environmental management as separate research streams. While some review articles have addressed sustainability in ports or the application of digital technologies in maritime logistics, they rarely focus specifically on how artificial intelligence contributes to measurable decarbonization outcomes within port environments. As a result, current knowledge lacks a consolidated understanding of how artificial intelligence techniques are applied across different port functions to reduce emissions and improve energy efficiency [2].

In addition, existing reviews often adopt either a qualitative synthesis or a bibliometric perspective in isolation. The absence of an integrated approach limits the ability to capture both the thematic depth of individual studies and the broader intellectual structure of the field. Without such integration, it is difficult to identify dominant research directions, evaluate the maturity of different artificial intelligence applications, and assess the extent to which current research supports practical decarbonization efforts in real-world port settings. This limitation is particularly important given the growing policy and industry pressure on ports to achieve measurable reductions in greenhouse gas emissions [3, 4].

Another limitation concerns the lack of systematic mapping between artificial intelligence methods, port operational domains, and environmental outcomes. Many studies report improvements in efficiency or predictive accuracy, but fewer establish a clear link between these improvements and quantifiable decarbonization impacts such as emission reduction or energy savings. This creates a gap between technological development and environmental performance assessment, which remains insufficiently addressed in the literature [5].

To address these limitations, this study adopts a combined systematic review and bibliometric analysis to provide a comprehensive and structured examination of AI-driven decarbonization strategies in maritime ports. The systematic review, guided by the PRISMA framework, enables a transparent and replicable selection and synthesis of relevant studies. The bibliometric analysis complements this approach by identifying influential authors, key research clusters, and the intellectual structure of the field. By integrating these two methods, the study moves beyond descriptive summarization and provides a more analytical understanding of how artificial intelligence contributes to port decarbonization.

The main contributions of this study are threefold. First, it provides a focused synthesis of recent peer-reviewed research on artificial intelligence applications specifically related to emission reduction and energy efficiency in port operations. Second, it identifies and organizes the literature into key thematic areas that reflect the dominant directions of research and technological development. Third, it highlights critical gaps that limit the practical implementation of AI solutions, including data constraints, lack of real-world validation, and limited integration across operational and environmental systems.

Based on these objectives, the study is guided by the following research questions:

- RQ1: What types of artificial intelligence techniques are applied to support decarbonization in maritime ports?
- RQ2: Which port operational areas are most frequently addressed by AI-driven decarbonization studies?
- RQ3: What bibliometric patterns define the intellectual and thematic structure of this research field?
- RQ4: What research and implementation gaps limit the effectiveness of artificial intelligence in achieving port decarbonization?

1.1 Conceptual Framework of AI-Driven Port Decarbonization

To provide a structured foundation for the analysis, this study adopts a conceptual framework that links artificial intelligence techniques to port operational processes and their associated decarbonization outcomes. The framework is developed to clarify how technological inputs are translated into environmental performance improvements within maritime port systems.

At the first level, artificial intelligence represents the enabling technological input. This includes a range of computational approaches such as machine learning, deep learning, neural networks, reinforcement learning, optimization algorithms, and emerging digital twin applications. These techniques are widely used to process large volumes of operational and environmental data, generate predictive insights, and support decision-making under complex and dynamic conditions.

At the second level, these artificial intelligence techniques are applied across key port operational domains. In this study, four primary domains are identified based on the literature synthesis. These include energy management, where artificial intelligence is used to forecast demand and optimize energy use; emission monitoring and prediction, where models estimate and track greenhouse gas emissions; operational optimization, where scheduling and resource allocation improve efficiency and reduce unnecessary fuel consumption; and renewable energy integration, where artificial intelligence supports the coordination of alternative energy sources within port systems.

At the third level, the application of artificial intelligence within these operational domains leads to measurable decarbonization outcomes. These outcomes include reductions in carbon dioxide emissions, improvements in energy efficiency, lower fuel consumption, and enhanced overall operational performance. The framework assumes that the effectiveness of these outcomes depends not only on the choice of artificial intelligence technique but also on the quality of data, the level of system integration, and the operational context of the port.

This conceptual structure provides a basis for organizing both the systematic review and the bibliometric analysis. It allows the study to examine not only which artificial intelligence methods are being used, but also how they are applied within port operations and to what extent they contribute to environmental sustainability objectives. Figure 1 below illustrates the conceptual framework of AI-driven port decarbonization.

Figure 1. Conceptual framework of AI-driven port decarbonization

2 Methodology

This study adopts a combined PRISMA-based systematic review and bibliometric analysis to examine AI-driven decarbonization strategies in maritime ports. Scopus served as the primary database due to its comprehensive coverage of peer-reviewed journals in engineering, environmental science, management, transport studies, and computer science.

2.1 Review Protocol

This study adopts a structured, systematic review combined with bibliometric analysis to examine the role of artificial intelligence in supporting decarbonization in maritime ports. The review process follows the PRISMA 2020 guidelines to ensure transparency, consistency, and reproducibility in the identification, screening, and selection of relevant studies.

The review protocol consists of five main stages. First, a comprehensive search strategy was developed to capture relevant literature across artificial intelligence, port operations, and environmental performance. Second, explicit inclusion and exclusion criteria were established to guide study selection. Third, a multi-stage screening process was conducted, including title, abstract, and full-text assessment. Fourth, bibliometric mapping was carried out using VOSviewer to identify key research patterns and the intellectual structure of the field. Finally, a thematic synthesis was conducted to examine how artificial intelligence contributes to emission reduction and energy efficiency in port environments.

2.2 Search Strategy

The Scopus database was selected as the primary source for this study due to its broad coverage of peer-reviewed journals and its strong representation of interdisciplinary research, particularly in engineering, environmental science, and transportation studies. Scopus is widely recognized for its comprehensive indexing and citation tracking capabilities, making it suitable for systematic reviews and bibliometric analysis [6, 7].

In addition, Scopus has been frequently used in similar systematic review studies related to artificial intelligence and sustainable transport systems, which supports its suitability for the present research context. Its structured metadata and compatibility with bibliometric tools such as VOSviewer further facilitate reliable network analysis and thematic mapping.

While the use of a single database may limit coverage of some publications, this approach ensures consistency in data extraction and analysis. The database selection is therefore considered appropriate for achieving the objectives of this study. Although the use of a single database may introduce limitations, this approach ensures consistency in data extraction and compatibility with bibliometric tools. Similar approaches have been adopted in maritime transport and port-related review studies. This limitation is acknowledged and discussed in the study.

The search was conducted in January 2026. A structured Boolean search query was developed to capture three main dimensions of the study: port context, artificial intelligence techniques, and decarbonization or emission-related outcomes. The search string applied in Scopus was as follows: ("port" OR "seaport" OR "maritime port" OR "container terminal") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "reinforcement learning") AND ("emission" OR "carbon" OR "decarbonization" OR "sustainability" OR "energy efficiency").

The search was limited to journal articles published between 2021 and 2025 and restricted to English-language publications. Although several recent 2026 publications are cited for contextual discussion purposes, only studies published between 2021 and 2025 were included in the systematic review dataset and bibliometric analysis.

2.3 Inclusion and Exclusion Criteria

The inclusion criteria were defined to ensure relevance to the research objectives. Only peer-reviewed journal articles published between 2021 and 2025 were considered. Studies were required to focus on port operations or port-related activities and to include the application of artificial intelligence techniques such as machine learning, deep learning, neural networks, reinforcement learning, or optimization methods. In addition, studies are needed to address environmental performance, including emission reduction, energy efficiency, or sustainability outcomes.

Studies were excluded if they focused solely on maritime shipping outside the port context, addressed digitalization without incorporating artificial intelligence techniques, or did not consider environmental or energy-related outcomes. Grey literature, conference papers, and non-English publications were also excluded to maintain consistency and quality.

2.4 Preferred Reporting Items for Systematic Reviews and Meta-Analyses Procedure

The study selection process followed the PRISMA 2020 framework, consisting of four stages: identification, screening, eligibility, and inclusion.

In the identification stage, a total of 165 records were retrieved from the Scopus database. No duplicate records were identified, resulting in 165 records proceeding to the screening stage.

During the screening stage, titles and abstracts were assessed against the inclusion criteria. A total of 100 records were excluded for several reasons, including studies focusing exclusively on maritime shipping without port-related applications, studies addressing general digitalization or automation without artificial intelligence techniques, articles unrelated to environmental performance or decarbonization objectives, and publications outside the defined document type or language criteria. This resulted in 65 articles being retained for full-text assessment.

In the eligibility stage, the remaining full-text articles were examined in detail to assess methodological suitability and relevance to the study objectives. Three articles were excluded because they did not provide sufficient methodological information regarding the artificial intelligence approach applied, or because the studies discussed sustainability concepts without establishing a direct connection to emission reduction, energy efficiency, or decarbonization outcomes within port operations.

Following this process, a final set of 62 articles met all inclusion criteria and was included in the systematic review. The PRISMA selection flow is illustrated in Figure 2.

2.5 Quality Assessment of Included Studies

To ensure the reliability and relevance of the selected studies, a study-level quality assessment was conducted. Each article was evaluated based on several criteria, including clarity of the artificial intelligence methodology, data source quality, validation approach, relevance to port decarbonization, and transparency of reporting.

Each criterion was assessed using a three-point scale, where 1 indicates low quality, 2 indicates moderate quality, and 3 indicates high quality. The evaluation was conducted systematically across all 62 included studies to ensure consistency. The quality assessment process was conducted independently by the authors based on the predefined evaluation criteria. To improve consistency and reduce potential bias, the scoring outcomes were cross-checked and discussed among the authors, and any differences in interpretation were resolved through consensus during the review process.

The purpose of this assessment was not to exclude studies but to provide an additional layer of methodological transparency and to support the interpretation of findings. A summary of the assessment criteria is presented in Table 1.

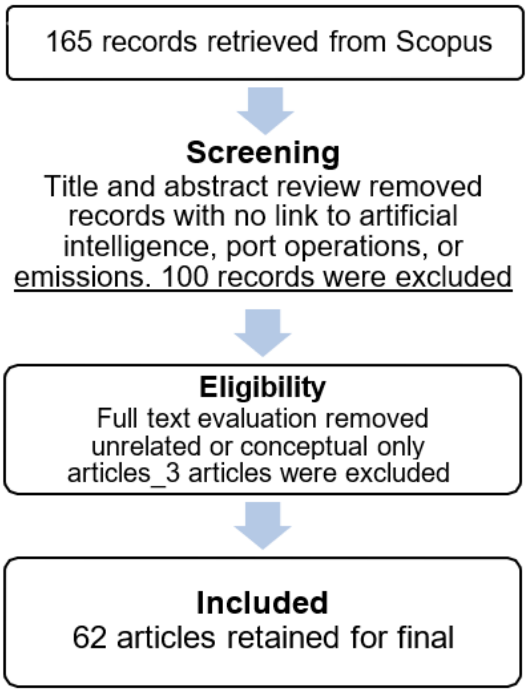

Figure 2. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) selection flow

Table 1. A summary of the assessment criteria

Criterion	Description	Score (1–3)
AI method clarity	Clear description of AI model, algorithm, and process	1 = unclear, 2 = partial, 3 = clear
Data quality	Source, size, and reliability of dataset	1 = weak, 2 = moderate, 3 = strong
Validation approach	Use of testing, benchmarking, or real-world validation	1 = none, 2 = limited, 3 = robust
Relevance to decarbonization	Direct link to emission reduction or energy efficiency	1 = weak, 2 = indirect, 3 = direct
Reporting transparency	Clarity in presenting results and limitations	1 = unclear, 2 = moderate, 3 = clear

To provide a clearer overview of study quality, an aggregated summary of the assessment results across the 62 included studies was developed based on the five evaluation criteria. The distribution of study quality levels is presented in Table 2.

The aggregated quality assessment indicates that the included studies generally demonstrated moderate to high methodological quality. AI method clarity was the strongest criterion, with most studies providing clear explanations of algorithms, modelling approaches, and analytical procedures. In contrast, the validation approach showed comparatively weaker performance, as many studies relied on simulation environments or secondary datasets rather than real-world port implementation. The assessment also indicates that while most studies addressed decarbonization objectives, the environmental impact was frequently measured indirectly through operational efficiency or energy optimization rather than direct carbon reduction metrics. Overall, the results suggest that the literature provides a solid methodological foundation, although further empirical validation and stronger integration between AI applications and measurable environmental outcomes remain necessary.

2.6 Bibliometric and Mapping Approach

Bibliometric analysis was conducted to complement the systematic review by providing a quantitative overview of the research structure and thematic development within the field. The analysis was performed using VOSviewer, which enables the construction and visualisation of bibliometric networks based on co-occurrence relationships among keywords.

Table 2. Aggregated quality assessment summary of included studies

Quality Criterion	High Quality	Moderate Quality	Low Quality	Main Observation
AI method clarity	39	19	4	Most studies clearly described the AI model, algorithm, and analytical process.
Data quality	28	26	8	Data quality varied across AI, sensor, operational, simulation, and secondary datasets.
Validation approach	18	30	14	Validation was often limited, with fewer studies using real-world port data.
Relevance to decarbonization	25	29	8	Many studies linked AI to decarbonization indirectly through efficiency or energy savings.
Reporting transparency	34	22	6	Most studies reported results clearly, although limitations were not always fully discussed.

The dataset used for bibliometric analysis consisted of the same 62 articles included in the final stage of the systematic review. Author keywords were extracted and standardised to ensure consistency. Synonymous terms and variations were harmonised through a manual cleaning process to avoid duplication and fragmentation of concepts.

A co-occurrence analysis of keywords was carried out to identify major research clusters. A minimum occurrence threshold of three was applied, meaning that only keywords appearing in at least three different articles were included in the analysis. This threshold was selected to balance the inclusion of relevant concepts while excluding rarely used or highly specific terms that do not contribute to broader thematic patterns.

The study used the full counting method, where each occurrence of a keyword was given equal weight. This approach was chosen to capture the overall prominence of research topics within the dataset. Network visualisation was generated using the association strength normalisation method, which is commonly applied in bibliometric studies to ensure that the strength of relationships between keywords is not biased by frequency differences.

Clustering was conducted automatically by VOSviewer using its built-in modularity-based algorithm, which groups keywords into clusters based on their co-occurrence relationships. These clusters represent distinct but related thematic areas within the literature. The resulting clusters were then interpreted and aligned with the thematic findings of the systematic review.

The bibliometric analysis provides a structural perspective of the research landscape, highlighting dominant research areas and their interconnections. When combined with the systematic review, it enables a more comprehensive understanding of how artificial intelligence applications in port decarbonization are distributed across different domains and how these domains evolve over time.

3 Bibliometric Results

This section presents the bibliometric findings obtained through VOSviewer analysis. The results include descriptive publication trends, influential journals, keyword co-occurrence patterns, co-cited authors, and co-cited references. These findings illustrate the intellectual structure, thematic directions, and research evolution of AI-driven decarbonization studies in maritime ports.

3.1 Descriptive Publication Analysis

A total of 62 studies were included after applying PRISMA screening. Figure 3 shows that the number of publications increased significantly from 2021 to 2025, reflecting growing research interest in artificial intelligence applications for port decarbonization.

The observed publication growth corresponds closely with several major global sustainability initiatives, notably the updates to the International Maritime Organization's (IMO) Greenhouse Gas (GHG) Strategy, the implementation of smart port digitization programs, and the European Union's Fit for 55 environmental agenda. Research outputs in this area are predominantly disseminated across a range of subject categories, including Environmental Science, Engineering, Transportation, Computer Science, and Business and Management, reflecting the multidisciplinary nature of efforts to enhance sustainability and efficiency in port operations.

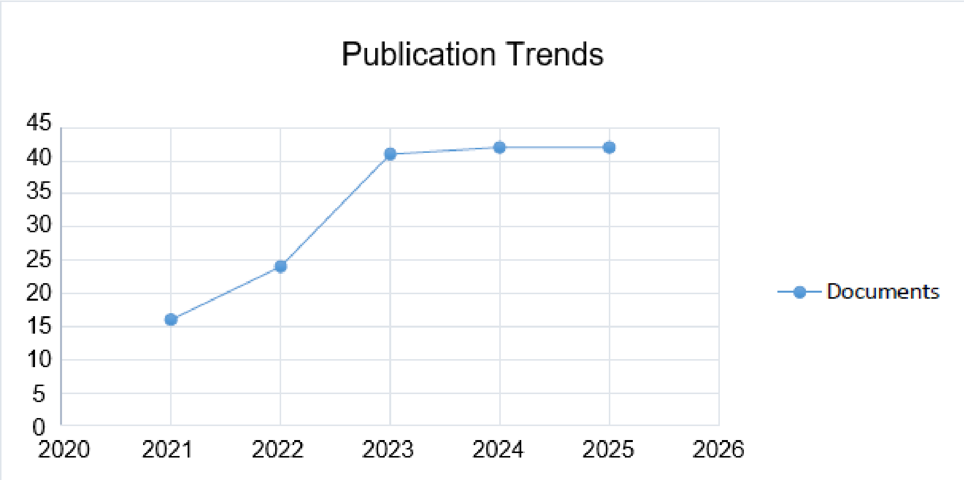

Figure 3. Annual publication trends for the year 2021–2025

3.2 Leading Journals and Publication Sources

The most active journals in this domain are those focusing on sustainability, port logistics, maritime operations, and energy management. Table 3 presents a summary of the most productive journals represented in the dataset.

Table 3. Most productive journals in the dataset

Journal	Relevance to Topic	Observation
Sustainability	Broad coverage of environmental and digital topics	Highest representation
Energy	Focus on energy systems and emissions	Core journal for energy-AI models
Marine Pollution Bulletin	Addresses environmental impacts from maritime operations	Frequently cited
Ocean and Coastal Management	Covers coastal logistics and environmental strategy	Moderate representation
Transportation Research Part E	Highly ranked for logistics and modeling	Key source of optimization work

These journals demonstrate a multidisciplinary interest that spans engineering, environmental management, and smart port operations.

3.3 Keyword Co-Occurrence Analysis

The analysis of keyword co-occurrence highlights the clustering of research themes within the field. According to the VOSviewer output, the most frequently occurring terms include "container terminal," "maritime port," "seaport," "machine learning," "sustainability," "optimization," "sustainable development," and "crane." Examination of the clustering patterns reveals four prominent thematic groups.

Cluster 1: Operational Optimization

This cluster addresses topics such as quay crane scheduling, berth allocation, container handling, and truck appointment systems.

Cluster 2: Energy Management

Focused on renewable energy integration, microgrids, energy efficiency measures, and AI-based load forecasting.

Cluster 3: Emission Monitoring and Prediction

Encompasses CO_2 estimation, greenhouse gas forecasting, near-real-time emission analysis, and the identification of emission hotspots.

Cluster 4: Smart Port Digitalization

Covers areas including digital twin models, IoT-enabled systems, intelligent automation, and predictive analytics, reflecting the integration of advanced technologies in port operations.

Figure 4 illustrates the keyword co-occurrence network generated through VOSviewer, highlighting the most frequently connected research themes across the selected studies. Among the strongest recurring terms were container terminal, container, port terminal, maritime port, seaport, crane, sustainability, sustainable development, optimization, and machine learning. The VOSviewer keyword map presents a wide and interconnected landscape of research themes that appear across the selected studies. The larger nodes, especially those related to container terminals, optimization, sustainability, and sustainable development, show that these topics appear most consistently in the literature. The map also divides naturally into several color-based clusters, each representing a different research focus. One cluster gathers terms linked to operational efficiency in container handling and terminal management. Another highlights themes related to energy use, environmental performance, and sustainable development in ports. A further cluster brings together studies that examine emission patterns, carbon management, and predictive modelling. There is also a group of terms associated with digital transformation in port operations, including automated systems, guided vehicles, and various decision-making tools. The dense connections across the clusters illustrate how these themes often overlap, suggesting that research on artificial intelligence for port decarbonization is becoming increasingly integrated across operational, environmental, and technological perspectives.

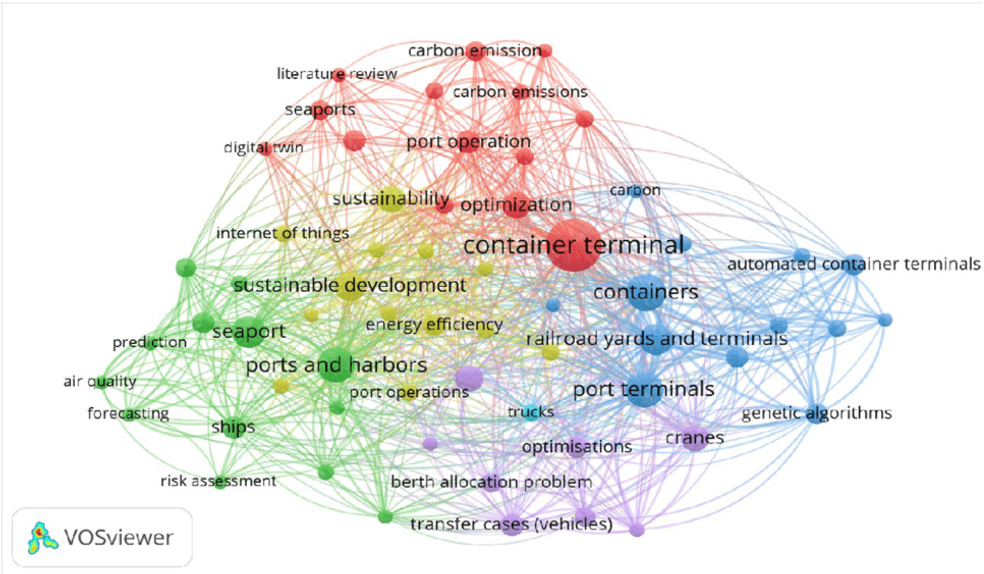

Figure 4. Keyword co-occurrence network map (VOSviewer)

3.4 Author Co-Citation Analysis

The author co-citation analysis highlights the most influential contributors within the research domain. Hector J. Carlo stands out as the central figure, with the highest citation count and strong co-citation connections, indicating a key role in linking multiple research streams. Huynh, Nathan N. and Sifakis, N. K. are also highly cited, reflecting their significant impact, although their co-citation links suggest more specialized or independent contributions. Authors such as Chen, Wei-Hsin, Bergqvist, Rickard Y., and Al-Dhaheri, Noura A. demonstrate meaningful co-citation integration, representing collaborative nodes that connect different clusters within the network. Overall, the analysis reveals a structured network dominated by central authors driving the intellectual discourse, alongside smaller interconnected groups contributing to emerging themes, thereby providing insight into the field's scholarly landscape. Table 4 provides a summary of the results of the author co-citation analysis.

Figure 5 demonstrates that the co-citation network shows that Carlo, Hector J. is the most influential and central author in the dataset, indicated by the largest node size and the highest total link strength (TLS). This author serves as the main bridge connecting all other researchers in the network. Al-Dhaheri, Noura A., shows a strong secondary link to Carlo, reflecting high co-citation frequency and close intellectual association. Authors such as Vis, Iris F. A., Chen Wei-Hhsin, Bergqvist Rickard Y., Notteboom, Theo E., and Huynh, Nathan N. are moderately connected to the core network, suggesting their contributions align with the central research themes represented by Carlo. Meanwhile, authors with no direct co-citation links (TLS = 0) appear as isolated nodes, indicating that although they contribute to the domain, their works are not frequently cited together with others in this dataset. Overall, the structure highlights Carlo, Hector J., as the key intellectual anchor around which the research domain is organized, with varying levels of peripheral influence among the remaining authors.

3.5 Interpretation of Co-citation Clusters

The co-citation analysis using VOSviewer reveals four distinct clusters, reflecting the intellectual structure of research in port operations, sustainability, and emission reduction.

Table 4. Author co-citation analysis

Author	Citations	Total Link Strength (TLS)	Interpretation of Link Strength
Carlo, Hector J.	11	4	Most influential; central in co-citation network.
Huynh, Nathan N.	7	1	Highly cited; contributes significantly to the field.
Sifakis, Nikolaos K.	6	0	Highly cited; specialized influence.
Chen, Wei-Hsin	4	1	Moderately cited; integrated within collaborative networks.
Bergqvist, Rickard Y.	4	1	Moderate influence and connectivity.
Al-Dhaheri, Noura A.	3	3	Moderate citations; strong co-citation integration.
Banister, David J.	3	0	Moderate citation; specialized influence.
Cullinane, Kevin P. B.	3	0	Moderate citation; isolated co-citation network.
Notteboom, Theo E.	3	1	Moderate citations; connected within co-citation clusters.
Vis, Iris F. A.	3	1	Moderate citations; part of smaller collaborative networks.

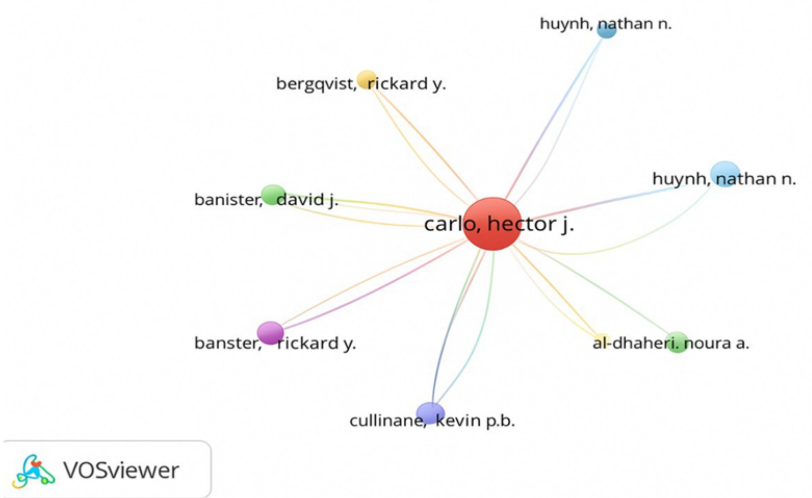

Figure 5. Author co-citation network map (VOSviewer)

Cluster 1: Terminal Operations and Operations Research (OR Cluster)

This cluster, represented by green–yellow nodes including Bierwirth, Carlo, Steenken, and Hsu, forms the methodological backbone of container terminal studies. It highlights foundational operational research literature addressing berth allocation, quay crane scheduling, yard optimization, dynamic resource assignment, and automated terminal operations. The high TLS of these references indicates that modern studies on port efficiency frequently build on these well-established OR methodologies, making this cluster the most influential within the dataset.

Cluster 2: Port Sustainability, Energy Efficiency, and Decarbonization

The red cluster, featuring authors such as Alamoush, Alzahrani, Acciaro, and Iris, emphasizes environmental management in ports, including greenhouse gas emissions, energy efficiency, and sustainability frameworks. While the TLS values are moderate, this cluster reflects the increasing integration of sustainability concerns into port research. It signals a growing research domain where environmental and decarbonization strategies are steadily becoming central to port studies.

Cluster 3: Truck Appointment Systems and Gate Emission Management

This smaller, green cluster, represented by Abdelmagid, Chen, and Giuliano, focuses on truck appointment systems, gate congestion, and truck-related emissions. Despite being distinct and problem-specific, it shows a well-defined research stream. Central references like Abdelmagid demonstrate stronger interlinkages within this cluster, highlighting the specialized focus on managing truck movements and reducing associated emissions.

Cluster 4: General Maritime Policy and Conceptual References

This minor cluster contains references with relatively low TLS values that provide broader conceptual, policy, and statistical context for port research. Unlike the operational and sustainability-focused clusters, these references are less interconnected within the co-citation network, indicating their supporting rather than central role in the development of the field.

Overall, the co-citation network shows that port research is structured around three main domains: operational research for terminal efficiency (the most influential), sustainability and decarbonization (emerging and growing), and truck emissions management (focused and specialized). The minor fourth cluster offers broader policy and conceptual foundations that complement these core areas.

4 Systematic Review Results

After completing the PRISMA screening process, a total of 62 studies were retained for detailed analysis. These studies were reviewed to gain a deeper understanding of how artificial intelligence is being applied to reduce emissions, enhance energy efficiency, and support sustainability-driven decision-making in maritime ports. From this synthesis, four key thematic areas emerged:

- The use of AI to support energy management,
- The use of AI for monitoring, predicting, and regulating emissions,
- The use of AI in operational improvements that indirectly reduce carbon output, and
- The use of AI in emerging work on renewable and alternative energy integration. The themes are described below.

4.1 Theme 1: AI for Energy Management in Ports

Energy consumption remains a major contributor to emissions in port operations, particularly through shore power systems, terminal lighting, cargo handling equipment, and microgrid infrastructure [8–10]. Recent studies increasingly apply artificial intelligence to improve port energy efficiency through more accurate demand forecasting, optimized energy allocation, and better coordination of multiple power sources [11–13].

A dominant application within this theme is energy demand forecasting. Supervised learning models are widely used to predict short-term and daily electricity consumption, enabling ports to manage peak loads and reduce unnecessary energy use [14–16]. In parallel, neural network- based approaches are employed to estimate vessel arrival patterns and associated shore power demand, improving capacity planning and reducing operational uncertainty [11–13].

While these approaches demonstrate strong predictive capability, an important distinction emerges between forecasting accuracy and actual decarbonization impact. Several studies report improvements in prediction performance, yet only a subset explicitly evaluates how these improvements translate into measurable energy savings or emission reduction. This suggests that forecasting models are technically mature, but their effectiveness depends on integration with operational decision-making systems.

Beyond forecasting, artificial intelligence is applied to optimize energy systems, particularly within port microgrids. These systems integrate renewable sources such as solar and wind with storage and grid supply, where artificial intelligence coordinates energy flows to reduce curtailment and limit dependence on fossil fuels [8, 11, 17, 18]. Compared to forecasting applications, optimization-based approaches show a stronger and more direct link to energy efficiency, as they actively influence how energy is distributed and consumed.

The reviewed studies also highlight clear differences in how various artificial intelligence approaches are applied within operational port environments. Machine learning and neural network approaches are predominantly used for forecasting and pattern recognition tasks because of their ability to process large volumes of operational and energy-related data with high predictive accuracy. In contrast, optimization-based and reinforcement learning approaches are more frequently associated with real-time decision support and adaptive energy allocation within dynamic port environments. These findings indicate that predictive models are more suitable for analytical and monitoring functions, whereas optimization-oriented approaches provide stronger operational control capability. Furthermore, studies using real-time operational datasets generally demonstrate greater practical relevance compared to simulation-based models, although such real-world implementations remain relatively limited across the literature.

In addition, artificial intelligence is applied at the operational level to improve the energy efficiency of equipment. Predictive models identify optimal operating windows for cranes and automated guided vehicles, reducing idle time and unnecessary energy use [19–22]. These applications illustrate how operational optimization and energy management are closely interconnected, with efficiency gains contributing indirectly to emission reduction.

Across the reviewed studies, there is evidence that artificial intelligence can deliver measurable improvements in energy performance. Several studies report reductions in energy consumption and carbon intensity when artificial intelligence tools are integrated into decision processes [23–26]. However, the magnitude and consistency of these improvements vary depending on data quality, system integration, and the level of automation within port operations.

Overall, the literature on AI-driven energy management in ports demonstrates a moderate level of maturity, with forecasting applications showing strong technical development while optimization and microgrid applications provide more direct contributions to decarbonization outcomes. Nevertheless, the overall effectiveness of these systems remains dependent on the integration of predictive models into real-time operational environments.

4.2 Theme 2: AI for Emission Monitoring, Prediction, and Control

A significant body of research examines how artificial intelligence can support the monitoring, prediction, and management of emissions generated by port activities. Compared to energy management, this area shows a more direct connection to decarbonization because it explicitly addresses the measurement and assessment of environmental impact across vessels, trucks, and cargo handling operations [16, 27–29].

A wide range of modelling approaches is used to estimate emissions such as carbon dioxide, nitrogen oxides, and particulate matter. These include regression models, neural networks, and time series techniques, each offering different levels of complexity and data requirements [10, 23, 30, 31]. The integration of multiple data sources, including Automatic Identification System trajectories, sensor data, equipment logs, and environmental conditions, allows for near-real-time emission estimation and improved situational awareness [15, 32, 33].

Although these approaches consistently demonstrate high predictive accuracy, important differences emerge in terms of model applicability and data dependency. Neural network-based models are effective in capturing complex relationships between operational variables and emission outputs, particularly when large and detailed datasets are available [30, 34, 35]. In contrast, regression and time series models are often used in situations where data availability is limited, offering greater simplicity but potentially lower precision [31, 36]. This indicates a trade-off between model sophistication and practical implementation, where highly accurate models may not always be feasible in data-constrained port environments.

Comparative analysis across the reviewed studies also reveals important differences in operational applicability between artificial intelligence approaches. Deep learning and neural network models generally achieve higher predictive performance when large and continuous datasets are available, particularly in ports with advanced digital infrastructure and integrated sensor systems. However, these approaches often require substantial computational resources and data standardisation, which may limit implementation in smaller or less technologically developed ports. In contrast, regression-based and hybrid statistical models demonstrate lower computational complexity and greater implementation flexibility, although they may offer lower predictive precision under highly dynamic operational conditions. This suggests that the effectiveness of artificial intelligence for emission monitoring is strongly influenced not only by model capability but also by the technological readiness and data maturity of the port environment.

A clear pattern across the reviewed studies is the separation between emission prediction capability and operational emission control. A large proportion of studies focus on estimating emissions with high accuracy, yet fewer studies extend these models to support operational decision-making. For example, while emission models are used to quantify environmental impact during vessel berthing and cargo handling, their integration into decisions such as berth allocation or equipment scheduling remains limited. This gap suggests that current research is largely focused on diagnostic capability rather than actionable intervention [33, 34].

Truck-related emissions provide a clearer example of how artificial intelligence can support both prediction and control. Predictive traffic models and clustering approaches are used to optimize gate scheduling and identify emission hotspots, reducing congestion and idle time [37–40]. In this case, emission reduction is more directly achieved because predictive insights are linked to operational adjustments.

Despite these advances, the overall effectiveness of emission monitoring systems remains strongly influenced by data quality and consistency. Several studies highlight challenges related to fragmented datasets, inconsistent reporting standards, and limited data granularity, which reduce model reliability and hinder cross-port comparison [26, 28, 33, 36]. These limitations suggest that technical capability alone is not sufficient, and that improvements in data infrastructure are essential for scaling artificial intelligence applications.

From an analytical perspective, the literature demonstrates strong technical capability in emission estimation and predictive modelling, although the integration of these systems into real-time operational decision-making remains relatively limited. Artificial intelligence significantly improves emission estimation and diagnostic capability, yet its contribution to decarbonization depends on the extent to which predictive models are integrated into real-time decision-making processes. Future research should therefore focus on linking emission prediction with control mechanisms and developing integrated systems that translate analytical outputs into measurable environmental outcomes.

4.3 Theme 3: AI for Operational Optimization with Indirect Decarbonization Effects

A large proportion of the reviewed studies investigate how artificial intelligence can improve operational efficiency in port systems, where decarbonization is achieved indirectly through lower fuel consumption and reduced operational delays. Although many studies do not explicitly quantify emission reductions, the operational improvements reported have clear environmental implications [41–44].

A major area of application is berth allocation, where artificial intelligence models are used to minimise vessel waiting time and improve scheduling efficiency. Studies consistently show that improved berth allocation reduces idle time at anchorage, which directly lowers fuel consumption and associated emissions [42, 45, 46]. Compared to other applications, berth allocation demonstrates a clear and immediate link between operational optimization and environmental benefit.

Quay crane scheduling represents another well-developed application. AI-driven optimization models enhance equipment utilisation and reduce energy consumption during cargo handling operations [47–49]. These studies indicate that improvements at the equipment level contribute to both productivity gains and energy efficiency, although emission reductions are often inferred rather than directly measured.

More advanced approaches involve reinforcement learning and adaptive optimization for yard crane and automated guided vehicle dispatching. These models enable dynamic decision-making under changing operational conditions, reducing idle time and inefficient routing [19–21, 50]. Compared to static optimization models, these approaches provide greater flexibility and responsiveness, although their effectiveness depends on continuous data availability and higher levels of digital infrastructure.

The reviewed studies also demonstrate a clear distinction between conventional optimization approaches and adaptive artificial intelligence models in terms of operational responsiveness and scalability. Static optimization models are generally effective under stable operational conditions and are easier to implement within existing port management systems. However, reinforcement learning and adaptive scheduling approaches provide greater flexibility in responding to dynamic vessel arrivals, equipment utilisation changes, and congestion conditions in real-time. These adaptive approaches appear particularly suitable for large and highly automated terminals where operational variability is significant. Nevertheless, their effectiveness depends heavily on continuous data availability, system interoperability, and advanced digital infrastructure. As a result, while adaptive artificial intelligence models offer stronger long-term optimization potential, conventional optimization methods may remain more practical for ports with limited technological readiness.

Truck-related operations further illustrate the operational impact of artificial intelligence. Predictive models are used to stabilise arrival patterns and optimize gate operations, reducing congestion and associated emissions [37, 39, 40, 51]. In this case, emission reduction is more directly observable because operational adjustments can be implemented immediately based on predictive insights.

In addition, predictive maintenance has emerged as a complementary application. Artificial intelligence is used to anticipate equipment failures and reduce unnecessary warm-up cycles, thereby lowering fuel consumption and improving energy efficiency [45, 52, 53]. This highlights how maintenance optimization can also contribute to indirect decarbonization.

Despite the strong evidence supporting operational optimization, an important limitation lies in the indirect nature of its environmental impact. Many studies focus on performance metrics such as throughput, delay reduction, or cost efficiency, without explicitly quantifying emission reductions. As a result, the magnitude of decarbonization benefits is often assumed rather than measured, which limits comparability across studies.

Analytically, among the four thematic areas identified, operational optimization appears to be the most mature and extensively developed stream of research. It is supported by a large number of studies and demonstrates consistent operational benefits across different port contexts. However, its contribution to decarbonization remains largely efficiency-driven rather than emission-focused. Future research should therefore prioritise the integration of environmental metrics into optimization models, allowing operational decisions to be evaluated not only in terms of efficiency but also in terms of their direct impact on emissions.

4.4 Theme 4: AI for Renewable and Alternative Energy Integration

Recent research increasingly explores how artificial intelligence can support the transition toward renewable and alternative energy systems within port environments. Compared to the previous themes, this area is less mature but more closely aligned with long-term decarbonization strategies, particularly in the context of energy transition and the adoption of low-carbon fuels [9, 16, 36].

A key application within this theme is the management of renewable energy systems. Artificial intelligence models are used to forecast energy generation from solar and wind sources and to optimize the scheduling of these resources within port microgrids [8, 11, 15]. These models improve the reliability of renewable integration by addressing variability in energy supply and aligning it with fluctuating port demand. Compared to conventional energy management approaches, artificial intelligence enables more adaptive and efficient coordination between renewable sources, storage systems, and grid supply.

In addition to renewable energy scheduling, artificial intelligence is applied to support the adoption of alternative fuels, including hydrogen and other low-carbon energy carriers. Predictive models are used to estimate fuel demand, optimize storage, and support bunkering operations under uncertain conditions [10, 23, 24]. These applications highlight the potential of artificial intelligence to facilitate structural changes in port energy systems. This moves beyond incremental efficiency improvements toward deeper decarbonization pathways.

In contrast to operational optimization and emission monitoring applications, renewable and alternative energy integration remains at a relatively early stage of implementation maturity. Most studies within this theme rely on simulation-based modelling, pilot projects, or scenario analysis rather than full-scale operational deployment. This reflects the higher infrastructure complexity and investment requirements associated with renewable integration and alternative fuel systems. In addition, the effectiveness of artificial intelligence in this context depends not only on predictive capability but also on coordination across multiple energy sources, storage technologies, and regulatory frameworks. Consequently, while this theme demonstrates strong long-term decarbonization potential, large-scale implementation may progress more slowly than operational optimization applications that can be integrated into existing port systems with fewer structural changes.

Another developing area involves the application of artificial intelligence in carbon capture and energy system optimization. Studies explore how predictive and optimization models can improve the efficiency of carbon capture processes and reduce energy losses within port-related systems [16, 18, 54]. While these approaches demonstrate strong theoretical potential, most remain at the simulation or pilot stage, with limited evidence of large-scale implementation.

Despite its potential, this theme is characterised by several limitations. Many studies rely on scenario-based modelling or case-specific data, which limits generalisability and makes it difficult to assess long-term performance. In addition, the integration of artificial intelligence with physical energy infrastructure requires significant investment, coordination, and technological readiness, which may constrain adoption across different port contexts.

Although research in this area is still developing, the literature suggests that renewable and alternative energy integration will play a strategically important role in long-term port decarbonization. Unlike operational optimization and emission monitoring, which focus on improving existing systems, renewable and alternative energy integration represents a shift toward fundamentally different energy structures. Artificial intelligence plays a key enabling role in this transition by supporting forecasting, optimization, and system coordination. However, further research is needed to validate these applications in real-world settings and to develop scalable solutions that can support port-wide energy transformation.

4.5 Consideration of Meta-Analysis

A statistical meta-analysis was deemed unsuitable due to heterogeneity in AI techniques, data types, and evaluation criteria [16, 29, 36, 55]. Only a limited number of studies reported directly comparable performance indicators [15, 33, 42]. Due to this heterogeneity, quantitative synthesis was not feasible. Similar constraints have been noted in other systematic reviews on artificial intelligence applications.

4.6 Integration of Bibliometric and Systematic Review Findings

The integration of bibliometric analysis and systematic review findings provides a more comprehensive understanding of how artificial intelligence contributes to decarbonization in port systems. While the systematic review offers detailed insights into specific applications and operational contexts, the bibliometric analysis highlights broader research patterns and thematic relationships across the literature.

A clear correspondence can be observed between the keyword clusters identified through bibliometric mapping and the four thematic areas developed in the systematic review. The operational optimization cluster, which includes terms related to berth allocation, crane scheduling, and yard management, aligns directly with the third theme. This cluster appears as the most dominant in the bibliometric network, reflecting the large number of studies that focus on improving operational efficiency. This finding is consistent with the systematic review, where operational optimization represents the most mature and widely applied area, with strong evidence of efficiency gains and indirect emission reduction.

The energy management cluster corresponds to the first theme, where artificial intelligence is applied to forecast demand, optimize energy use, and manage microgrid systems. Keywords related to energy efficiency, renewable integration, and smart energy systems appear frequently, indicating growing attention to energy-related decarbonization strategies. The systematic review confirms that artificial intelligence improves forecasting accuracy and supports energy optimization, although the extent of direct emission reduction varies depending on how these models are integrated into operational processes.

The emission monitoring cluster aligns with the second theme, focusing on the prediction and analysis of environmental impact. Keywords such as carbon emissions, sustainability, and environmental performance are strongly represented, reflecting the increasing importance of emission measurement and reporting. The systematic review shows that artificial intelligence significantly enhances emission estimation capabilities, yet also highlights a gap between prediction and operational control. This suggests that, although the technical capability for emission monitoring is well developed, its integration into decision-making remains limited.

The cluster associated with digitalization and intelligent systems shows partial overlap with the fourth theme on renewable and alternative energy integration. While the bibliometric analysis groups concepts such as digital twins, automation, and smart systems under a broader digitalization perspective, the systematic review reveals that their application to renewable energy and alternative fuels is still emerging. This indicates that the transition toward low-carbon energy systems is gaining increasing attention but has not yet reached the same level of maturity as operational optimization or emission monitoring.

An important insight from this integrated analysis is the imbalance between research intensity and practical implementation. Operational optimization dominates both the bibliometric and systematic findings, indicating a well-established field with clear operational benefits. In contrast, renewable energy integration and alternative fuel applications are less represented and are often based on simulation or case-specific studies. This highlights a gap between short-term efficiency improvements and long-term decarbonization strategies.

Overall, the integration of bibliometric and systematic evidence strengthens the validity of the four thematic areas and provides a clearer picture of the research landscape. AI applications in port decarbonization are progressing from efficiency-driven optimization toward more comprehensive environmental and energy system integration. However, further development is required to connect these areas into unified and scalable solutions that can support practical implementation across different port contexts.

5 Discussion and Future Directions

This section brings together the insights obtained from both the bibliometric analysis and the systematic review. It interprets the consolidated evidence at a broader level, discusses remaining challenges in the literature, outlines implications for stakeholders, and highlights several directions that can guide future research on AI-based systems that enable decarbonization in maritime ports.

5.1 Synthesis of Key Findings

The overall evidence suggests that artificial intelligence applications in port decarbonization are gradually evolving from a primary emphasis on operational efficiency toward broader environmental and energy system integration. Although all four thematic areas contribute to emission reduction, they differ in terms of maturity, practical applicability, and direct environmental impact.

Operational optimization represents the most established area, supported by a large number of studies focusing on berth allocation, equipment scheduling, and traffic coordination [19, 42, 47]. These applications consistently demonstrate improvements in efficiency and reductions in fuel consumption. However, emission reductions are often inferred rather than explicitly measured, which suggests that environmental benefits are not always fully captured in existing models.

Emission monitoring and prediction provide a more direct pathway to decarbonization by quantifying environmental impact. Artificial intelligence significantly improves the accuracy and timeliness of emission estimation [28, 33]. Despite this progress, the transition from prediction to operational control remains limited, indicating that current applications are more diagnostic than decision-oriented.

Energy management occupies an intermediate position. Artificial intelligence is widely used for demand forecasting and energy optimization, particularly within microgrid systems [11, 15, 56]. While improvements in energy efficiency are evident, their impact on emission reduction depends on how predictive outputs are integrated into operational decision-making.

Renewable and alternative energy integration represents an emerging but strategically important area. Artificial intelligence supports renewable scheduling, alternative fuel adoption, and energy system coordination [10, 16, 56, 57]. However, most studies remain at the modelling or pilot stage, which limits the assessment of real-world performance.

Collectively, the reviewed studies demonstrate that artificial intelligence contributes to port decarbonization through both operational efficiency improvements and longer-term energy transition strategies. The effectiveness of these contributions depends on system integration, data availability, and the ability to translate predictive insights into actionable decisions.

A comparative perspective across the reviewed studies also reveals important differences in the operational applicability of artificial intelligence approaches within port environments. Predictive models such as machine learning and neural networks are widely used for forecasting energy demand, vessel arrivals, and emission patterns due to their strong analytical capability and high predictive accuracy. However, these approaches primarily support monitoring and planning functions rather than direct operational control. In contrast, optimization-based and reinforcement learning approaches demonstrate stronger applicability in dynamic operational settings, particularly for berth allocation, equipment scheduling, and traffic coordination, where real-time decision making is required. The review also indicates that simulation-based models remain dominant across the literature, while large-scale real-world implementation is still relatively limited. In practice, highly automated ports with advanced digital infrastructure appear better positioned to adopt adaptive artificial intelligence systems, whereas smaller or developing ports may continue to rely on simpler optimization and forecasting approaches due to limitations in data integration, technological readiness, and financial resources.

5.2 Key Research Gaps Identified

Despite the increasing volume of research, several important gaps remain. One of the most consistent limitations across the literature is the limited availability of real-world validation. Many studies rely on simulation or controlled datasets rather than operational data from active ports [16, 42, 58]. This limits confidence in scalability and long-term effectiveness.

Second, data fragmentation remains a major constraint. Differences in data quality, structure, and availability reduce model reliability and hinder cross-port comparison [10, 59]. This issue is particularly critical for emission monitoring and energy optimization applications.

Third, integration across systems is limited. Most studies focus on specific applications such as scheduling or prediction, without linking them into a unified framework. This prevents the development of port-wide decarbonization strategies [20, 34, 59, 60].

Fourth, model transparency remains a concern. Advanced artificial intelligence models often lack explainability, which may reduce trust among practitioners and decision makers [27, 37, 59, 61].

Finally, the geographical distribution of studies is uneven. Research is concentrated in developed regions, while ports in developing economies remain comparatively underrepresented in the literature [13].

5.3 Policy and Managerial Implications

The results provide several important implications for practice. For port authorities, artificial intelligence can support integrated environmental management by enabling real-time emission monitoring and improved coordination of operations [49, 57]. However, effective implementation requires investment in digital infrastructure and data integration systems.

For terminal operators, operational optimization offers a practical starting point for adopting artificial intelligence. Improvements in scheduling and resource allocation can deliver immediate efficiency gains and indirect emission reductions [14, 62]. At the same time, expanding the use of artificial intelligence toward energy management and emission monitoring can provide more direct environmental benefits.

For policymakers, the findings highlight the importance of data standardisation and technology support. Policies that promote data sharing, common reporting standards, and investment in digital systems can accelerate adoption [32, 45, 63–65]. It is also important to consider differences in technological readiness across regions.

Despite the potential benefits, the practical implementation of AI-driven decarbonization strategies presents several operational challenges. Ports differ significantly in terms of digital infrastructure, automation maturity, financial resources, and workforce capability, which may influence the scalability of artificial intelligence applications across different operational environments. Large and highly automated ports are generally better positioned to adopt advanced optimization and predictive systems due to stronger data integration capabilities and technological readiness. In contrast, smaller or developing ports may face difficulties related to fragmented data systems, limited interoperability between operational platforms, high implementation costs, and shortages of specialised technical expertise. These differences suggest that successful implementation requires not only technological investment but also organisational readiness, workforce training, and long-term coordination between port authorities, terminal operators, and regulatory agencies.

5.4 Limitations of the Study

This study has several limitations.

First, the analysis is based on Scopus-indexed journal articles, which may exclude relevant studies from other databases or industry sources. Although this ensures consistency, it may limit coverage.

Second, the diversity of artificial intelligence methods and evaluation approaches makes direct comparison difficult. Differences in datasets, model design, and performance metrics reduce generalisability [50, 55, 57].

Third, the review is based on published studies, which may introduce reporting bias since positive results are more likely to be reported.

5.5 Future Research Directions

Future research should focus on real-world implementation and validation of artificial intelligence applications using operational port data. This will improve understanding of long-term performance and scalability [13, 15, 60, 62, 63].

There is also a need for integrated models that combine operational optimization, emission monitoring, and energy management within a unified framework [28, 40].

Improving data standardisation and interoperability is another priority. Shared data platforms can enhance comparability and support wider adoption of artificial intelligence models [33, 64].

Finally, further research is needed on renewable energy systems, hydrogen, and alternative fuels, where empirical evidence remains limited but the potential impact is significant [10, 16].

6 Conclusion

This study examined how artificial intelligence is applied to support decarbonization in maritime ports by integrating a systematic review with bibliometric analysis. Based on the analysis of 62 peer-reviewed studies published between 2021 and 2025, the findings provide a structured understanding of how AI-driven approaches contribute to emission reduction across different operational and energy domains.

In relation to the research questions, this study provides several key insights. For RQ1, artificial intelligence techniques applied in port decarbonization include machine learning models, neural networks, optimization algorithms, and reinforcement learning approaches. For RQ2, these techniques are primarily used in energy management, emission monitoring and prediction, operational optimization, and renewable and alternative energy integration. For RQ3, the effectiveness of artificial intelligence varies across applications, with operational optimization demonstrating strong efficiency gains, while emission monitoring improves diagnostic capability but remains limited in decision integration. For RQ4, the main challenges include data fragmentation, lack of real-world validation, limited system integration, and differences in technological readiness across port contexts.

The results show that artificial intelligence is applied across four main areas, namely energy management, emission monitoring and prediction, operational optimization, and renewable and alternative energy integration. These areas differ in terms of maturity and impact. Operational optimization represents the most established field, where efficiency improvements lead to indirect emission reduction. Emission monitoring provides strong diagnostic capability but is not yet fully integrated into decision-making. Energy management shows growing application with variable environmental outcomes, while renewable and alternative energy integration remains an emerging area with significant long-term potential.

The main contribution of this study lies in the integration of thematic analysis and bibliometric mapping to provide both detailed and structural insights into the research landscape. By linking artificial intelligence techniques to port operations and decarbonization outcomes, the study offers a clearer understanding of how different approaches contribute to sustainability objectives. In addition, the study identifies key gaps related to data availability, system integration, and real- world validation, which limit the practical implementation of artificial intelligence solutions.

Overall, the findings indicate that artificial intelligence has strong potential to support port decarbonization, but its effectiveness depends on the ability to move from isolated applications toward integrated and scalable systems. Achieving this transition requires improvements in data infrastructure, closer alignment between predictive models and operational decision-making, and stronger collaboration between researchers and industry stakeholders. As ports face increasing pressure to reduce emissions, artificial intelligence is expected to play an increasingly important role in enabling more efficient and sustainable port systems.

Author Contributions

Conceptualization, A.Z. and A.M.A.; methodology, A.Z.; software, A.Z.; validation, S.A. and K.A.M.S.; formal analysis, A.Z.; investigation, A.Z.; resources, A.M.A.; data curation, A.Z.; writing—original draft preparation, A.Z.; writing—review and editing, S.A., K.A.M.S., D.L.R., and A.M.A.; visualization, A.Z.; supervision, A.M.A.; project administration, A.Z. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Declaration on the Use of Generative AI and AI-assisted Technologies

The authors used generative AI and AI-assisted technologies solely for language refinement, grammar checking, and improvement of sentence clarity during the preparation of this manuscript. All conceptual development, data collection, analysis, interpretation of results, and academic content were conducted entirely by the authors. The authors take full responsibility for the accuracy, originality, and integrity of the manuscript and confirm that generative AI tools were not used to fabricate data, generate false references, or replace the authors' intellectual contributions.

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