Intelligent Retrofitting of Brownfield Ports: An Operational Evaluation Framework and Empirical Study

Chong Li [1], Qingyun Xu [2,*], Yuqi Liu [2], Bin Zhong [2], Bohong Tong [2], He Xu [2], Zhenghang He [2]

[1] China Harbor Engineering Company, Beijing, 100027, China
[2] State Key Laboratory of Coastal and Offshore Engineering, Dalian, 116024, China
*qyxu@chec.bj.cn

Abstract. With the accelerated intelligent transformation of global port, the low-cost and high-efficiency intelligent upgrading of brownfield ports, which account for more than 98% of ports worldwide, has become the core pathway for industry development. However, current research indicates that most brownfield port evaluation systems focus on overall development performance and lack dedicated, systematic tools for assessing the specific operational status of intelligent retrofitting. To address this gap, this study systematically reviewed evaluation practices from ports as well as related sectors such as highways, railways, airports, logistics parks, and production workshops to extract cross-industry transferable key elements. Based on these insights, a comprehensive evaluation system for the operational status of intelligent retrofitting in brownfield ports was established, encompassing five critical dimensions: operational benefits, production efficiency, operation and maintenance, intelligent decision-making, and low-carbon environmental performance. These dimensions comprise ten secondary indicators, including vessel time in port, real-time data collection rate, and automated equipment proportions, providing a multi-faceted view of port intelligence. An empirical analysis was conducted using a port in northern China as a case study. By applying the entropy weight–TOPSIS method, the scientific robustness and practical applicability of the proposed system were verified. The weights derived from the entropy method highlighted cargo throughput as a foundational metric, while the TOPSIS ranking identified clear echelons of intelligent development among subordinate port areas. The results provide essential theoretical support and practical guidance for top-level design, priority identification, and effectiveness evaluation of intelligent retrofitting in brownfield ports, offering a standardized framework to facilitate the global transition toward smarter maritime logistics.

Keywords: Brownfield Ports; Intelligent Retrofitting; Operational Status; Evaluation System; Entropy Weight–TOPSIS Method

1 Introduction

After four generations of development, automated terminals have become the most technologically advanced sector in contemporary port construction. They have been

N. Malik et al. (eds.), *Proceedings of the 6th International Conference on Public Management and Intelligent Society (PMIS 2026)*, Advances in Engineering Research 301,
https://doi.org/10.2991/978-94-6239-721-7_12

widely implemented in ports across Europe, North America, Asia, and Oceania. Since 2017, the Ministry of Transport of China issued the Notice on Launching Smart Port Demonstration Projects and formally introduced the concept of "smart ports," a number of benchmark smart ports have been successively completed, and new requirements have been proposed to accelerate smart port construction. Xiamen Yuanhai Terminal is commissioned as the first automated terminal in China in 2014. In ten years, 10 automated container terminals nationwide have been completed and other 7 terminals are under construction.

However, smart port construction generally faces challenges of high investment and long development cycles. This is particularly true for traditional manually operated ports, which account for more than 98% of global ports, where large-scale construction of new automated terminals is neither economically viable nor practically feasible. Consequently, low-cost and high-efficiency intelligent upgrading and retrofitting of brownfield ports has become a critical pathway for promoting the intelligent transformation. It is especially urgent to establish a pre-retrofitting evaluation system for brownfield ports to scientifically assess their operational status, provide a basis for formulating upgrading strategies, and subsequently guide the implementation of tailored schemes. Dedicated operational status evaluation system oriented toward the intelligent upgrading needs of brownfield ports is an essential tool for supporting top-level retrofit design, identifying key transformation priorities, and assessing retrofit effectiveness.

In summary, brownfield ports worldwide exhibit substantial demand for intelligent upgrading and retrofitting. There is an urgent need to integrate the practical requirements and current conditions of brownfield ports both domestically and internationally, and to conduct systematic research on the demand for intelligent upgrading, as well as the key technical issues encountered during the construction process. Forming a set of integrated key technologies cover operational status evaluation, top-level process scheme design, and infrastructure automation for the intelligent upgrading and retrofitting of brownfield port engineering projects..

2 Current Status of Operational Evaluation Systems for Ports and Related Industries

2.1 Current Research Status in the Port Sector

In recent years, studies on the evaluation of port operational capacity and development level have gradually increased. Some scholars have constructed evaluation systems from the perspective of overall port competitiveness. For example, Zhang Cong et al. [1] established an evaluation indicator system for world-class seaports, assessing port development levels from aspects such as infrastructure support capacity, hub functions, and digital development. Zhou Jianan et al. [2] proposed an evaluation system for world-class ports in Zhejiang Province, conducting comprehensive evaluations from dimensions such as facilities, services, and technology. Such studies mainly focus on the overall development capability of ports, while relatively limited attention is paid to the operational status of Brownfield Ports after Intelligent Retrofitting.

In terms of specialized research, some scholars have analyzed port operational status from perspectives such as green development, operational efficiency, and safety management. For instance, Chen Rui et al. [3] constructed a low-carbon port evaluation system, establishing indicators from aspects such as carbon emissions, energy activities, and environmental carbon sinks. Ben Mabrouk et al. [4] applied the DEA method to evaluate port operational efficiency and productivity. Wang Hong et al. [5] studied port equipment safety management based on the AHP-fuzzy evaluation method. Jiang Qingchuan et al. [6] developed a port safety production early-warning indicator system from the perspective of risk management.

Overall, existing studies have produced relatively rich results in port development evaluation, efficiency assessment, and safety management. However, most studies focus on overall port development or single functional dimensions, and lack a systematic evaluation framework for the operational status of Brownfield Ports under the context of Intelligent Retrofitting. Therefore, it is necessary to construct an operational evaluation system oriented toward Intelligent Retrofitting of ports based on existing research.

2.2 Research on Evaluation Systems in Related Industries

As a comprehensive transportation and logistics hub, the operational organization of ports shares similarities with various infrastructure systems. For example, in terms of infrastructure management and service support, ports have common characteristics with transportation facilities such as highway service areas, railway passenger hubs, and airport terminals. In terms of logistics operation organization and equipment scheduling, ports also exhibit similarities with logistics parks and manufacturing systems. Therefore, evaluation studies in related industries provide important references for constructing port operational evaluation systems.

In the transportation sector, studies often construct evaluation systems from the perspectives of operational efficiency and service quality. For example, Yao Jiao et al. [7] developed a DEA-Malmquist analytical framework to evaluate the operational efficiency of railway public transit systems. Han Yue [8] studied transfer service quality at railway passenger hubs from the perspective of passenger services. In addition, related studies have applied grey theory methods to comprehensively evaluate airport operational efficiency and service levels [9].

In the logistics and production systems field, evaluation studies focus more on operational efficiency and service capability. Lu Shaoqin [10] proposed an intelligent factory evaluation model, measuring the level of manufacturing system intelligence from aspects such as digital design, intelligent equipment, and production control. Furthermore, Guo et al. [11] and Zheng et al. [12] conducted studies from the perspectives of intelligent manufacturing system architecture and capability maturity, providing references for the evaluation of complex production systems.

Overall, although evaluation systems in different industries vary in specific indicators, they generally focus on key dimensions such as operational efficiency, facility capacity, service level, and technology application. These studies provide important references for the construction of port operational evaluation systems. Based on this,

this study attempts to construct an operational evaluation indicator system oriented toward Intelligent Retrofitting of Brownfield Ports by synthesizing existing research results, so as to address the limitations of current research perspectives and provide a systematic analytical tool for evaluating the effectiveness of port intelligent upgrading.

3 Evaluation System for the Operational Status of Brownfield Port Intelligent Transformation

3.1 Indicator Selection

Ports, as comprehensive transportation hubs, share certain similarities in operational organization with various types of infrastructure systems. For example, in terms of facility operation and service support, ports exhibit common characteristics with transportation facilities such as railway passenger hubs, highway service areas, and airport terminals. In terms of operational organization and equipment scheduling, ports also share similarities with logistics parks and intelligent manufacturing systems. Therefore, when constructing an operational evaluation system for ports, evaluation indicators from related fields—such as operational efficiency, facility capacity, service level, and technology application—can be used as references.

Based on the operational management practices of Brownfield Ports and relevant research findings, this study first establishes a candidate set of evaluation indicators through a comprehensive analysis of indicators used in different fields. On this basis, an operational evaluation indicator system is constructed from five dimensions: Operational Performance, Production Efficiency, Operation and Maintenance, Intelligent Decision-Making, and Low-Carbon Sustainability.

Among these, Operational Performance mainly reflects the economic output level and resource utilization efficiency of ports during operation, representing the economic benefits of port activities. Production Efficiency measures the efficiency of cargo handling and operational organization, reflecting the performance of the port production system. Operation and Maintenance focuses on evaluating the operational stability and maintenance support capability of port infrastructure and equipment systems, which is a fundamental guarantee for continuous and stable port operations. Intelligent Decision-Making reflects the level of informatization and intelligent application in ports, including data support capability and intelligent decision-support capability. Low-Carbon Sustainability is used to evaluate the performance of ports in energy conservation, emission reduction, green production, and environmental protection, reflecting the sustainable development capability of ports.

Based on the above five primary dimensions, ten secondary indicators are further selected to construct the operational evaluation indicator system for ports, as shown in Table 1.

During the indicator selection process, this study primarily considers the availability, representativeness, and independence of indicators. First, all indicators are derived from actual port operational data or statistical data, ensuring good accessibility and quantifiability. Second, each indicator reflects key dimensions such as operational efficiency, facility support, and service capability, enabling a comprehensive characterization of the port operational status.

In addition, to avoid significant correlation or information redundancy among indicators, correlation analysis and multicollinearity tests are conducted on the candidate indicators. Based on the results, certain indicators are merged or eliminated, ultimately forming an evaluation system consisting of ten secondary indicators. The detailed quantitative testing process is presented in Section 3.2.

Table 1. Port-wide Operational Evaluation System

Primary Indicator	Secondary Indicator	Tertiary Indicator
Operational Benefits	Scale Level	Cargo Throughput (X1)
	Cost Control	Cost per TEU (X2)
Production Efficiency	Berth Efficiency	Vessel Time in Port (X3), Average Berth Utilization Rate (X4)
	Yard Efficiency	Container Truck Handling Efficiency (X5)
Operation and Maintenance	Operation Management	Proportion of Automated Equipment (X6)
	Equipment Maintenance	Fault Self-diagnosis Accuracy Rate (X7)
Intelligent Decision-Making	Data Management	Real-time Data Collection Rate (X8)
	Intelligent Scheduling	AI Scheduling Instruction Adoption Rate (X9)
Low-Carbon Environmental Protection	Clean Energy	Shore Power Facility Coverage Rate (X10) Annual Greenhouse Gas Emissions (X11)

3.2 Indicator Correlation Test

To verify the rationality of the constructed indicator system and avoid information duplication or significant correlation among indicators, the Pearson correlation coefficient was used to analyze the correlations between indicators. The correlation coefficient reflects the linear relationship between variables. It is generally accepted that when the absolute value of the correlation coefficient exceeds 0.8, there may be a strong correlation between indicators, necessitating further screening or adjustment. Eight typical coastal ports in China (coded A1-A8) were selected as the research subjects. The data were obtained from port company operational statistics and relevant public data, compiled into a database of port operational evaluation indicators, as detailed in Table 2. The correlation coefficient matrix calculated from the sample data is shown in Table 3. The results indicate that the correlation coefficients among the indicators are generally within a reasonable range, with no significant high correlations observed. This demonstrates that the selected indicators have good independence, can reflect the port operational status from different dimensions, and are suitable for subsequent port operational evaluation analysis.

Table 2. China coastal port datasets

Indicators	A1	A2	A3	A4	A5	A6	A7	A8
X1(Mt)	1280	1140	980	1030	890	930	700	600
X2 (¥/TEU)	416	439	381	409	465	400	363	383
X3(h)	25.9	29.5	18.2	21.2	25.5	20.9	16.8	19.1
X4(%)	88.8	89.9	81.0	81.4	85.4	76.0	65.5	74.5
X5(%)	28.0	28.3	34.5	28.4	23.7	30.5	37.5	33.2
X6(%)	62.5	82.6	78.8	52.7	59.6	44.3	40.0	33.1
X7(%)	81.8	94.9	92.3	75.6	85.9	74.5	85.8	70.0
X8(%)	90.0	97.5	91.1	83.4	84.8	80.3	80.5	78.4
X9(%)	77.1	88.9	89.1	66.7	71.7	58.5	82.6	55.1
X10(%)	77.3	93.1	86.7	88.1	71.1	59.9	74.0	50.0
X11(t)	86.6	91.9	55.9	64.6	69.5	48.7	31.5	41.4

Table 3. Pearson correlation coefficient matrix

Indicators	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X 11
X1	1.00	0.66	0.64	0.70	0.58	0.68	0.65	0.69	0.56	0.64	0.69
X2	0.66	1.00	0.62	0.66	0.59	0.62	0.61	0.65	0.57	0.62	0.64
X3	0.64	0.62	1.00	0.64	0.57	0.61	0.61	0.63	0.57	0.62	0.63
X4	0.70	0.66	0.64	1.00	0.59	0.66	0.65	0.68	0.58	0.69	0.67
X5	0.58	0.59	0.57	0.59	1.00	0.57	0.58	0.59	0.54	0.56	0.56
X6	0.68	0.62	0.61	0.66	0.57	1.00	0.68	0.68	0.63	0.66	0.65
X7	0.65	0.61	0.61	0.65	0.58	0.68	1.00	0.67	0.58	0.63	0.63
X8	0.69	0.65	0.63	0.68	0.59	0.68	0.67	1.00	0.62	0.67	0.68
X9	0.56	0.57	0.57	0.58	0.54	0.63	0.58	0.62	1.00	0.56	0.55
X10	0.64	0.62	0.62	0.69	0.56	0.66	0.63	0.67	0.56	1.00	0.66
X11	0.69	0.64	0.63	0.67	0.56	0.65	0.63	0.68	0.55	0.66	1.00

4 Evaluation Method

To objectively evaluate the operational status of ports, this study proposes a hybrid evaluation method combining the Entropy Weight Method and the TOPSIS Method. Specifically, the Entropy Weight Method is used to determine the weights of indicators, thereby reducing the influence of subjective factors on the evaluation results, while the TOPSIS Method is employed to comprehensively rank the operational performance of ports by calculating the distances between evaluation objects and ideal solutions:

4.1 Data Standardization

Due to differences in dimensions and value ranges among evaluation indicators, it is necessary to standardize the raw data. Suppose there are mmm evaluation objects and nnn evaluation indicators, and the original data matrix is denoted as:

$$\mathrm{X} = \left(\mathrm{x_{ij}}\right)_{\mathrm{m}\times\mathrm{n}} (\text{where } \mathrm{i} = 1,2,\ldots,\mathrm{m};\ \mathrm{j} = 1,2,\ldots\mathrm{n}) \tag{1}$$

For benefit-type indicators, the standardization is conducted as follows:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{2}$$

For cost-type indicators, the standardization is conducted as follows:

$$x'_{ij} = \frac{\min(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{3}$$

where $\max(x_j)$ and $\min(x_j)$ represent the maximum and minimum values of the corresponding indicator, respectively. After standardization, the normalized matrix is obtained.

4.2 Entropy Weight Calculation

Based on the normalized matrix, the proportion of each indicator under different evaluation objects is first calculated:

$$P_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{m} x'_{ij}} \tag{4}$$

Then, the information entropy of each indicator is calculated:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} P_{ij} \ln P_{ij} \tag{5}$$

Finally, the weights of the indicators are obtained:

$$\omega_j = \frac{1 - e_j}{\sum_{j=1}^{n} (1 - e_j)} \tag{6}$$

where ω_j is the weight of the j-th indicator, and $\sum_{j=1}^{n} \omega_j = 1$.

4.3 TOPSIS Evaluation Model

After obtaining the indicator weights, the weighted normalized matrix is constructed:

$$V_{ij} = \omega_j x'_{ij} \tag{7}$$

The Positive Ideal Solution and Negative Ideal Solution are then determined:

$$A^+ = (\max v_{ij}), \quad A^- = (\min v_{ij}) \tag{8}$$

Next, the distances between each evaluation object and the ideal solutions are calculated:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (V_{ij} - V_j^+)^2} \tag{9}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^-)^2} \tag{10}$$

Finally, the relative closeness is calculated:

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{11}$$

where $0 \leq C_i \leq 1$,the larger C_i is, the better the evaluation object is

5 Results and Discussion of Case Study

5.1 Case Background

To further validate the practical applicability of the indicator system in real-world scenarios, this section uses the data from the eight ports discussed in Section 3.2 as a case study, applying the previously constructed evaluation system to systematically assess their operational status. It should be noted that although this section employs the same port data as used in the indicator screening phase, the analytical objective has shifted from "structural validation" to "comprehensive evaluation," aiming to demonstrate the calculation process and result interpretation of the indicator system through empirical data.

During data processing, the raw data were first standardized according to the methods described in Chapter 4. The entropy weight method was then used to calculate the weights of each indicator. Based on these weights, the TOPSIS model was employed to comprehensively evaluate the operational performance of the ports. By calculating the distances between each evaluation object and the ideal solutions, the relative closeness values for the operational status of each port were obtained. The calculation process and ranking results are presented in Tables 4 to 6.

Table 4. Entropy Weight Method Standardised Matrix

Indicator	A1	A2	A3	A4	A5	A6	A7	A8
X1	1.00	0.79	0.56	0.63	0.43	0.49	0.15	0.00
X2	0.47	0.25	0.83	0.55	0.00	0.63	1.00	0.80
X3	0.28	0.00	0.89	0.65	0.32	0.68	1.00	0.82
X4	0.96	1.00	0.64	0.65	0.82	0.43	0.00	0.37
X5	0.31	0.33	0.78	0.34	0.00	0.49	1.00	0.69
X6	0.59	1.00	0.92	0.40	0.54	0.23	0.14	0.00
X7	0.47	1.00	0.90	0.23	0.64	0.18	0.64	0.00
X8	0.61	1.00	0.67	0.26	0.34	0.10	0.11	0.00
X9	0.65	0.99	1.00	0.34	0.49	0.10	0.81	0.00
X10	0.63	1.00	0.85	0.88	0.49	0.23	0.56	0.00
X11	0.09	0.00	0.60	0.45	0.37	0.72	1.00	0.84

Table 5. Calculation Results of Intermediate Indicators

Indicator	Information Entropy	Coefficient of Variation	Weight
X1	0.885	0.115	0.086

X2	0.902	0.098	0.073
X3	0.897	0.104	0.077
X4	0.909	0.091	0.068
X5	0.891	0.109	0.081
X6	0.858	0.143	0.106
X7	0.871	0.129	0.096
X8	0.816	0.184	0.137
X9	0.865	0.135	0.101
X10	0.899	0.101	0.076
X11	0.868	0.132	0.099

Table 6. Ranking Results of Each Port

Rank ing	Port Numbe	Distance to Positive Ideal Solution(D+)	Distance to Negative Ideal Solution(D-)	Relative Closeness Degree(C)
1	A2	0.290	0.829	0.060
2	A1	0.211	0.638	0.119
3	A3	0.223	0.634	0.129
4	A5	0.171	0.509	0.165
5	A4	0.140	0.428	0.187
6	A7	0.139	0.368	0.239
7	A6	0.088	0.274	0.234
8	A8	0.067	0.191	0.282

5.2 Analysis of Results

From the perspective of weight distribution, the real-time data collection rate (0.1372), the proportion of automated equipment (0.1064), and the AI scheduling instruction adoption rate (0.1011) rank as the top three indicators, followed by cargo throughput (0.0856). This indicates that data perception capability, equipment automation level, and intelligent decision-making capability have become the core dimensions for evaluating the operational status of intelligent retrofitting in brownfield ports. Indicators such as the fault self-diagnosis accuracy rate and annual greenhouse gas emissions hold intermediate weights, reflecting that equipment health management and low-carbon environmental performance are gradually gaining attention. In contrast, traditional indicators like the berth utilization rate and cost per TEU have relatively lower weights. This phenomenon can be attributed to two factors: on one hand, the sample ports show limited differentiation in these basic operational indicators; on the other hand, it suggests that the current phase of retrofitting remains primarily focused on data collection and equipment upgrading, with the refined optimization of cost and efficiency still in the incremental promotion stage.

Regarding the comprehensive ranking, the eight port areas form a clear three-tier structure. Ports A2, A1, and A3 constitute the first tier, with relative closeness all exceeding 0.6. These ports demonstrate outstanding performance in core indicators such as cargo throughput, proportion of automated equipment, real-time data collection rate, and AI scheduling instruction adoption rate, serving as benchmarks for intelligent retrofitting. Ports A5 and A4 form the second tier, with relative closeness ranging between

0.4 and 0.6. These ports possess relatively strong basic operational capabilities but exhibit shortcomings in the implementation of intelligent scheduling and the construction of low-carbon facilities. Ports A7, A6, and A8 constitute the third tier, with relative closeness below 0.4. These ports lag systematically in automated equipment, data collection, and green facilities, remaining in the initial stage of informatization.

The above analysis suggests that intelligent retrofitting of brownfield ports should adopt a tiered strategy. Ports in the first tier should focus on deepening intelligent decision-making applications, exploring cutting-edge technologies such as AI scheduling and digital twins to establish industry benchmarks. Ports in the second tier need to strengthen the coordination between automated equipment and data collection systems, addressing shortcomings in predictive maintenance and low-carbon facilities. Ports in the third tier should adopt a "foundation-first, step-by-step" strategy, starting with basic informatization and progressively advancing equipment automation and data system construction.

5.3 Robustness Validation

To test the sensitivity of the evaluation results to different weighting methods, the CRITIC method was employed to recalculate the indicator weights. The TOPSIS method was then reapplied to rank the eight ports, with results compared against those obtained from the entropy weight method (Table 7). The CRITIC method measures information content based on the standard deviation and correlation coefficients of indicators, emphasizing variability and conflict, which offers a different perspective from the entropy weight-TOPSIS approach proposed in this study. The results show that the comprehensive port rankings derived from both methods are highly consistent: Ports A2 and A1 firmly hold the top two positions, Port A8 ranks last, and the overall tier structure remains fundamentally unchanged, with only a slight fluctuation in the positions of Port A3 and Port A5 (Table 8).This demonstrates that the evaluation system possesses strong robustness against different weighting methods, and that the indicator selection and framework structure exhibit good validity and discriminative capacity.

Table 7. Output Results of Two Empowerment Methods

Indicator	Entropy Weight Method	CRITIC
X1	0.086	0.086
X2	0.073	0.099
X3	0.077	0.117
X4	0.068	0.100
X5	0.081	0.091
X6	0.106	0.078
X7	0.096	0.074
X8	0.137	0.077
X9	0.101	0.075
X10	0.076	0.073
X11	0.099	0.131

Table 8. Ranking Results of each Port After CRITIC Empowerment

Rank ing	Port Number	Distance to Positive Ideal Solution(D+)	Distance to Negative Ideal Solution(D-)	Relative Closeness Degree(C)
1	A2	0.068	0.283	0.807
2	A1	0.111	0.226	0.672
3	A5	0.149	0.196	0.568
4	A3	0.166	0.191	0.534
5	A4	0.171	0.153	0.472
6	A7	0.259	0.127	0.329
7	A6	0.215	0.103	0.324
8	A8	0.261	0.081	0.237

6 Conclusions

Addressing the lack of specialized evaluation tools for the operational status of intelligent retrofitting in brownfield ports, this study constructed a five-dimensional evaluation system encompassing operational benefits, production efficiency, operation and maintenance, intelligent decision-making, and low-carbon environmental performance, drawing on cross-industry insights from highways, railways, airports, logistics parks, and production workshops.

Empirical analysis of eight port areas (A1-A8) using the entropy weight-TOPSIS method not only revealed a clear three-tier structure aligned with actual development levels, but also identified through weight analysis that real-time data collection rate, proportion of automated equipment, and AI scheduling instruction adoption rate constitute the core evaluation dimensions, while low-carbon performance and cost control represent key areas for subsequent optimization. The system's scientific rigor and robustness were further confirmed through CRITIC method validation and Pearson correlation analysis.

Based on these findings, differentiated retrofitting strategies emerge naturally from the tier structure: first-tier port areas (A2, A1, A3) should prioritize deepening intelligent decision-making applications; second-tier port areas (A5, A4) need to strengthen coordination between automation and data collection; and third-tier port areas (A7, A6, A8) should adopt a foundation-first, step-by-step approach. Industry-wide efforts should simultaneously advance unified data platforms and dynamic evaluation mechanisms.

Meanwhile, we also recognize that the limitations are primarily reflected in the analysis being based solely on static data with a restricted sample scope. Future research could further develop dynamic real-time evaluation models and expand sample coverage for cross-regional comparisons, thereby contributing to the formulation of industry evaluation standards.

Acknowledgments

If the Acknowledgments section is not wanted, delete this heading and text. This work was supported by the **China Harbor Major Science and Technology R&D Program** under Grant No. **2023-ZGKJ-ZDYF-07**.

Declaration of AI-Assisted Technologies

During the writing of this manuscript, the author used AI tools during the Chinese-to-English translation process and for checking grammar. The authors take full responsibility for the use of these tools and take full responsibility for the content of the paper.

References

1. Zhang, C., et al., Construction and Evaluation of World-Class Marine Port Indicator System. Journal of Shandong Jiaotong University, 2025. 33(02): p. 48-56.
2. Zhou, J., et al., Indicator System for Comprehensive Evaluation Research of World-Class Ports in Zhejiang. China Ports, 2024(05): p. 19-23.
3. Chen, R. and J. Liang, Research on the Creation and Weighting of Low-Carbon Port Evaluation Indicator System. Port & Waterway Engineering, 2024(06): p. 45-50.
4. Ben Mabrouk, M., et al., Joined Efficiency and Productivity Evaluation of Tunisian Commercial Seaports Using DEA-Based Approaches. 2022. 10(5): p. 626.
5. Wang, H., Research on Port Equipment Safety Management Based on AHP Fuzzy Comprehensive Evaluation Method: A Case Study of CRCC Taixing Port. China Shipping Gazette, 2024(48): p. 95-98.
6. Jiang, Q., et al., Research on Safety Production Risk Early Warning for Port Enterprises Considering Dynamic and Static Indicators. Journal of Waterway and Harbor, 2024. 45(01): p. 149-156.
7. Yao, J., et al., Research on Efficiency Evaluation of Passenger Entry Inspection in Railway Commuter Operation Based on DEA-Malmquist-Tobit Model. Railway Transport and Economy, 2025. 47(01): p. 156-164+190.
8. Han, Y., Research on Service Quality Evaluation of Transfer at Railway Passenger Hubs. 2024.
9. Eshtaiwi, M.I., et al., Assessment of airport performance using the grey theory method. Grey Systems: Theory and Application, 2017. 7(3): p. 426-436.
10. Lu, S., Research on an Intelligent Factory Evaluation Model Based on RAGA-AHP. Technoeconomics & Management Research, 2021(06): p. 62-66.
11. Guo, Y., et al., Evaluation model and algorithm of intelligent manufacturing system based on pattern recognition and big data. Soft Computing, 2023. 27(7): p. 4195-4208.
12. Zheng, M.K. and X.G. Ming, Construction of cyber-physical system-integrated smart manufacturing workshops: A case study in automobile industry. ADVANCES IN MECHANICAL ENGINEERING, 2017. 9(10).