International Journal of Computer Science and Information Technology (IJISIT)
Volume 2, No. 2 (2025) pp. 144-152
e-ISSN 3063-4156 | p-ISSN 3063-4172
DOI: 10.55123/ijisit.v2i2.53

Intelligent Decision Support Systems for Maritime Human Resource Planning: Predictive Analytics for Seafarer Workforce Supply and Demand Forecasting

Nurindah Dwiyani[1], Mukhlas Hamdani[2], Derma Watty Sihombing[3], Rosna Yuherlina Siahaan[4], Nazilul Hamidi[5]
[1,2,3,4,5]Maritime Institute, Sekolah Tinggi Ilmu Pelayaran Jakarta, North Jakarta, Indonesia

Article Info

Article history:

Received October 03, 2025
Revised November 21, 2025
Accepted December 30, 2025

Keywords:

Decision Support Systems
Maritime Human Resources
Predictive Analytics
Seafarer Supply
Workforce Planning

ABSTRACT

Intelligent decision support systems leveraging predictive analytics and artificial intelligence offer transformative capability for maritime human resource planning through accurate forecasting of seafarer workforce supply and demand dynamics, enabling proactive training capacity adjustment, recruitment strategy optimization, and policy intervention to address emerging labor market imbalances. This study investigates AI-powered workforce forecasting system implementation for Indonesian maritime education planning through convergent mixed-methods research combining quantitative predictive model development with qualitative stakeholder consultation. Historical workforce data spanning 2010-2023 were analyzed using ARIMA time series, Random Forest regression, and LSTM neural networks to forecast officer supply-demand dynamics. Focus Group Discussions with maritime education administrators (n=11), industry employers (n=14), and government workforce planning officials (n=8) explored forecast utilization barriers and integration mechanisms. Findings demonstrate that ensemble machine learning models achieve 86.2 percent accuracy at 3-year horizons and 80.4 percent accuracy at 5-year horizons in predicting seafarer workforce gaps, providing actionable intelligence for strategic planning. However, institutional inertia, data infrastructure inadequacy, and planning horizon misalignments constrain forecast adoption despite technical capability. The study proposes an Intelligent Maritime Workforce Planning Framework integrating predictive analytics platforms, unified maritime workforce data systems, multi-horizon forecast generation, and accountability structures for forecast-responsive decision-making.

Corresponding Author:

Nurindah Dwiyani
Maritime Institute,
Sekolah Tinggi Ilmu Pelayaran Jakarta,
14150, North Jakarta, Indonesia
Email: nurindah05kammar@gmail.com

1. INTRODUCTION

Maritime workforce planning confronts a fundamental temporal mismatch between the time required to produce qualified seafarers and the speed with which industry labor demand fluctuates. When a shipping company identifies the need for additional deck officers to crew an expanding fleet, those officers cannot be instantaneously produced—they must be recruited into maritime academies, trained through multi-year programs, certified through STCW examinations, and accumulate sea service before achieving professional competency. This 4 to 6 year production pipeline means that workforce planning decisions made today will only generate labor market effects half a decade later, creating urgent need for accurate long-term forecasting that enables proactive rather than reactive adjustment to emerging supply-demand imbalances [1].

Traditional maritime workforce planning has relied primarily on retrospective analysis—examining historical enrollment trends, current employment levels, and reported industry vacancies to infer future needs. This backward-looking approach struggles to anticipate the non-linear dynamics that characterize contemporary maritime labor markets: technological disruptions reducing crew requirements through automation, regulatory changes mandating new competencies, economic shocks triggering sudden fleet expansions or contractions, and demographic transitions as aging seafarer cohorts retire [2]. The maritime industry's global character further complicates forecasting, as seafarers trained in one nation frequently serve on vessels flagged in other jurisdictions, creating labor market interdependencies that transcend national planning boundaries. International shipping's vulnerability to geopolitical disruptions, trade pattern shifts, and environmental regulations introduces additional volatility that confounds linear projection methodologies [3].

Intelligent decision support systems employing machine learning predictive analytics can process vastly larger datasets incorporating economic indicators, shipping industry trends, regulatory developments, and demographic projections to generate probabilistic forecasts of future workforce supply-demand balances with accuracy and temporal horizon impossible through manual analysis [4]. These systems learn complex patterns from historical data, identifying non-obvious relationships between predictor variables and workforce outcomes that enable anticipation of demand shifts before they manifest in current employment statistics. By continuously updating predictions as new data become available, AI-powered forecasting systems provide dynamic intelligence that evolves with changing conditions rather than static projections that quickly become obsolete [5].

The theoretical foundation for intelligent workforce forecasting rests on convergence of several analytical traditions. Human capital theory establishes that workforce investment decisions should be guided by anticipated future returns, making accurate demand forecasting essential for efficient resource allocation [6]. Systems thinking emphasizes the interconnectedness of workforce development components—recruitment, training, certification, employment, retention, and retirement—requiring holistic modeling that captures feedback loops and time delays throughout the talent pipeline [7]. Labor economics contributes equilibrium analysis frameworks for understanding how supply-demand imbalances generate wage adjustments, employment fluctuations, and migration patterns that ultimately restore market balance, albeit often at substantial economic and social cost if imbalances are severe [8].

Advanced forecasting methodologies have evolved considerably over recent decades. Early workforce planning relied on simple linear extrapolation of historical trends, assuming that past growth rates would continue indefinitely into the future. More sophisticated approaches incorporated demographic cohort analysis, tracking aging workforce populations through retirement cycles to predict replacement demand [9]. Contemporary AI-powered forecasting transcends these limitations by employing machine learning algorithms capable of identifying complex, non-linear relationships between multiple predictor variables and workforce outcomes. Time series models such as ARIMA capture temporal dependencies and seasonal patterns in historical data. Ensemble methods like Random Forest regression integrate multiple predictor variables—economic indicators, industry capacity, regulatory changes, technological disruptions—to generate multivariate forecasts. Deep learning architectures including Long Short-Term Memory (LSTM) neural networks model long-term dependencies and capture intricate patterns that simpler algorithms miss [10].

Indonesia faces particularly acute maritime workforce planning challenges as the world's fourth-largest seafarer-supplying nation while simultaneously experiencing rapid domestic maritime sector growth. The International Labour Organization estimates that Indonesian seafarers comprise approximately 8 percent of the global maritime workforce, with over 200,000 Indonesians serving aboard international and domestic vessels [11]. STIP Jakarta and Indonesian maritime education institutions must balance international seafarer export markets—where Indonesian officers compete globally with Filipino, Chinese, Indian, and Eastern European counterparts—with domestic fleet officer requirements for the expanding national shipping, ferry, and offshore sectors. This dual market orientation creates complex planning dynamics: international demand fluctuates with global shipping cycles, flag state policies, and competitive positioning against other seafarer-supplying nations, while domestic demand responds to Indonesia's archipelagic connectivity initiatives, maritime infrastructure development, and cabotage enforcement requiring Indonesian-flagged vessels crewed by Indonesian nationals [12].

Accurate forecasting of both international and domestic demand, calibrated against institutional training capacity and enrollment pipeline dynamics, is essential for avoiding either officer oversupply (generating unemployment and depressed wages) or shortage (constraining fleet growth and maritime economic development). Historical episodes of workforce imbalance illustrate the consequences of inadequate planning. During the 1970s and 1980s, many European maritime nations expanded academy capacity in response to strong contemporary demand, only to face severe oversupply when technological advances reduced crew requirements and flags of convenience shifted employment opportunities to lower-cost seafarer-supplying nations [13]. Conversely, rapid growth in specialized sectors such as offshore oil and gas, cruise operations, and LNG transport has periodically generated acute officer shortages in specific competency areas, constraining industry expansion and driving wage inflation [14].

Yet despite these demonstrated risks and the availability of increasingly sophisticated forecasting technologies, no systematic intelligent forecasting system currently operates to guide Indonesian maritime workforce planning decisions, which remain largely reactive to current rather than projected conditions. Maritime academy enrollment decisions are driven primarily by facility capacity constraints and political pressure to expand access to vocational education, with limited systematic analysis of labor market demand signals. Industry hiring needs are communicated through ad hoc surveys and anecdotal reports rather than continuous demand monitoring systems. Government workforce planning agencies lack integrated data infrastructure linking academy enrollments, graduation rates, employment placements, industry hiring demand, and fleet capacity trends into unified platforms that would enable evidence-based forecasting and policy adjustment [15].

This institutional and technical gap motivates the present study's investigation of AI-powered workforce forecasting capabilities and adoption requirements. While the technical literature demonstrates that machine learning algorithms can achieve high prediction accuracy for skilled labor markets, maritime-specific applications remain limited, and even fewer studies examine the organizational transformation challenges that determine whether technical forecasting capability translates into improved planning practice. Indonesian maritime workforce planning provides an ideal context for investigating these questions due to the sector's substantial economic importance, the documented challenges of balancing dual international and domestic markets, and the absence of existing intelligent forecasting systems that could be leveraged for planning improvement.

This study investigates the development and validation of AI-powered workforce forecasting models for Indonesian maritime education planning, examining predictive accuracy across multiple machine learning algorithms, identifying optimal forecasting methodologies for maritime workforce applications, and proposing integration frameworks for embedding predictive analytics into institutional and national maritime workforce policy decision-making processes. By combining quantitative model development and validation with qualitative stakeholder consultation on forecast interpretation and utilization, the research generates both technical performance benchmarks and organizational implementation insights essential for transitioning from reactive to predictive workforce planning.

The study is guided by the central research question: What predictive accuracy can AI-powered forecasting models achieve for Indonesian seafarer workforce supply-demand dynamics, and how can these forecasts be effectively integrated into maritime education planning and policy decision-making processes? This question encompasses both technical validation of forecasting algorithms and organizational analysis of adoption barriers and integration mechanisms, recognizing that forecast utility depends not merely on predictive accuracy but on institutional capacity and willingness to utilize predictions for proactive planning adjustment.

2. METHODS

This study employed a convergent mixed-methods research design integrating quantitative predictive model development and validation with qualitative Focus Group Discussions exploring forecast utilization and decision-making integration [16]. The quantitative stream developed machine learning forecasting models using historical workforce data and validated their predictive accuracy through out-of-sample testing against actual subsequent outcomes. The qualitative FGD stream generated stakeholder perspectives on forecast interpretation, confidence thresholds required before triggering policy action, and institutional barriers to data-driven planning. This mixed-methods approach enabled comprehensive investigation addressing both the technical question of forecasting accuracy and the organizational question of forecast adoption and integration into planning processes.

Historical workforce data were obtained from multiple authoritative sources covering the 2010-2023 period, providing 14 years of observations sufficient for robust model training and validation. Indonesian seafarer employment data came from the Directorate General of Sea Transportation, which maintains records of certificate of competency issuance and seafarer employment placement. STIP Jakarta and national maritime academy enrollment and graduation records provided annual cohort sizes by program, rank, and specialization. Shipping industry officer demand data came from annual surveys conducted by the Indonesian Ship Owners Association polling member companies on hiring needs and vacancy rates. Global seafarer labor market context was established through BIMCO/ICS international workforce reports documenting worldwide supply-demand trends and competitive dynamics among seafarer-supplying nations [17].

Key variables extracted from these data sources included annual officer graduations disaggregated by rank (deck and engineering officers at management and operational levels) and program specialization, employment placement rates tracking the percentage of graduates securing positions within 12 months, industry hiring demand expressed as reported vacancies and expansion hiring plans, fleet capacity trends measured by gross tonnage and vessel numbers in Indonesian and international fleets employing Indonesian officers, and demographic retirement projections based on age cohort analysis of the active seafarer workforce. These variables collectively captured both the supply side (academy production) and demand side (industry hiring needs) of the workforce equation, along with the demographic transitions that drive replacement demand as aging cohorts retire.

Three distinct forecasting algorithms were developed to enable comparative performance evaluation and ensemble modeling. ARIMA (AutoRegressive Integrated Moving Average) time series models were specified to capture temporal dependencies, seasonal patterns, and trend dynamics in historical workforce data. Model selection employed the Box-Jenkins methodology involving identification, estimation, and diagnostic checking of alternative ARIMA specifications, with optimal models selected based on Akaike Information Criterion minimization [18]. Random Forest regression models were constructed to integrate multiple predictor variables through ensemble decision tree algorithms that reduce overfitting risk while capturing complex non-linear relationships. Hyperparameter tuning optimized tree depth, minimum split requirements, and ensemble size through cross-validation performance assessment. Long Short-Term Memory (LSTM) neural networks were architected to model long-term dependencies in sequential data through recurrent connections and gating mechanisms that selectively retain or discard information across time steps, enabling capture of intricate temporal patterns that simpler algorithms miss [7].

All models were trained on data from 2010-2018 and validated against actual outcomes from 2019-2023, providing out-of-sample testing that avoids overfitting bias and enables realistic assessment of forecasting performance on previously unseen data. Forecast horizons of 3 and 5 years were evaluated, matching the planning cycles relevant to maritime academy capacity decisions. Model performance was assessed using multiple metrics: prediction accuracy measured as percentage of forecasts within ±10 percent of actual outcomes, Mean Absolute Error (MAE) quantifying average prediction deviation in absolute terms, and Root Mean Square Error (RMSE) penalizing larger prediction errors more heavily than small deviations. Analysis was conducted using Python 3.9 with statsmodels library for ARIMA implementation, scikit-learn for Random Forest regression, and TensorFlow for LSTM neural network development [4].

For the qualitative FGD phase, three stakeholder groups were purposively sampled to represent the key decision-making perspectives relevant to workforce forecasting adoption. Maritime education administrators from STIP Jakarta and other Indonesian academies responsible for enrollment planning, curriculum development, and facility capacity decisions (n=11) provided institutional planning perspectives. Maritime industry employers including shipping companies and manning agencies who hire graduating officers and face the direct consequences of supply-demand imbalances (n=14) contributed demand-side insights on forecast utility and commitment challenges. Government workforce planning officials from the Ministry of Transportation's Directorate General of Sea Transportation and the Ministry of Manpower's vocational training coordination division (n=8) offered policy and regulatory perspectives on system-level workforce planning integration.

Four FGD sessions of 90-110 minutes each were conducted during August-September 2023 in Jakarta, with sessions organized to enable both within-group deliberation and cross-stakeholder comparison. Sessions explored three thematic areas: interpretation of forecast outputs and translation into planning implications, confidence thresholds and accuracy requirements stakeholders would need before committing to forecast-responsive policy actions, and institutional barriers to data-driven planning including organizational culture, data infrastructure, and governance structure challenges. FGD protocols employed semi-structured discussion guides while allowing emergent themes to be explored. Sessions were audio-recorded, transcribed verbatim, and analyzed using thematic analysis following Braun and Clarke's systematic approach involving data familiarization, initial coding, theme identification, theme review, and definition [19]. Coding was conducted independently by two researchers with discrepancies resolved through discussion to enhance analytic rigor.

3. RESULTS

The integrated analysis of forecasting model performance and stakeholder deliberations revealed that AI-powered workforce forecasting achieves sufficient accuracy for strategic planning while generating important institutional insights about the data infrastructure, analytical capacity, and decision-making culture transformations required for effective forecast utilization. Results are presented first for quantitative model performance, followed by qualitative FGD findings on organizational adoption dynamics.

Table 1 presents predictive model performance across the three algorithms and their ensemble combination for the 2019-2023 validation period.

Table 1. AI Forecasting Model Performance: Seafarer Workforce Supply-Demand Prediction (2019-2023 validation period)

Forecasting Algorithm	3-Year Accuracy	5-Year Accuracy	Mean Absolute Error	RMSE	Best Application
ARIMA Time Series	81.3%	74.2%	287 officers	342	Stable trend continuation
Random Forest Regression	84.7%	78.6%	231 officers	289	Multi-variable integration
LSTM Neural Network	82.9%	76.8%	254 officers	308	Long-term dependencies
Ensemble Model	86.2%	80.4%	218 officers	271	Comprehensive forecasting

Note: Accuracy = percentage of forecasts within ±10% of actual outcomes. MAE = Mean Absolute Error in officers. RMSE = Root Mean Square Error.

The ensemble model combining all three algorithms achieved the highest accuracy (86.2 percent at 3-year horizons, 80.4 percent at 5-year horizons), demonstrating that machine learning can reliably forecast workforce dynamics with sufficient precision for strategic enrollment planning, facility investment, and recruitment strategy decisions. The mean absolute error of 218 officers means the model's predictions typically deviate from actual outcomes by fewer than 220 officers annually in a total workforce pipeline of approximately 12,000—a 1.8 percent error rate indicating high practical utility for planning purposes. Even at the more challenging 5-year horizon, accuracy remains above 80 percent, providing actionable intelligence with sufficient lead time for the most substantial capacity adjustments such as new academy development or major program expansions.

Individual algorithm performance revealed distinct strengths matching their theoretical capabilities. ARIMA time series models performed best when historical trends continued relatively smoothly without major disruptions, achieving 81.3 percent 3-year accuracy. However, ARIMA struggled with structural breaks such as the COVID-19 pandemic's impact on seafarer employment during 2020-2021, demonstrating the limitations of purely time-dependent forecasting. Random Forest regression achieved the highest individual algorithm performance (84.7 percent at 3 years) by integrating multiple predictor variables including fleet capacity trends, economic indicators, and regulatory changes, enabling anticipation of demand shifts driven by factors beyond historical workforce trends alone. LSTM neural networks captured long-term dependencies and complex temporal patterns, performing particularly well for 5-year horizons where intricate multi-period dynamics become more influential.

Table 2 presents the stakeholder-deliberated decision framework linking forecast scenarios to recommended planning actions and required confidence thresholds.

Table 2. Stakeholder Decision Framework: Forecast Confidence Thresholds and Planning Actions (N=33 participants)

Forecast Scenario	Predicted Gap	Confidence Level	Recommended Action	Lead Time Required
Severe Officer Shortage	>500 officers/year	≥80%	Enrollment expansion, new academy development	5+ years
Moderate Shortage	200-500 officers	≥75%	Accelerated recruitment, curriculum efficiency	3-4 years
Balanced Supply-Demand	±200 officers	≥70%	Maintain current capacity	Ongoing monitoring
Moderate Oversupply	200-500 officers	≥75%	Enrollment restraint, alternative sector pivots	3-4 years
Severe Oversupply	>500 officers/year	≥80%	Program suspension consideration	5+ years

Note: Confidence Level = minimum forecast accuracy required before triggering policy response. Lead Time = planning horizon required for full implementation.

This framework demonstrates stakeholder recognition that more severe predicted imbalances require higher forecast confidence before triggering major policy interventions, reflecting appropriate caution about committing to irreversible decisions based on uncertain projections. The achieved ensemble model accuracy of 86.2 percent at 3 years and 80.4 percent at 5 years exceeds the confidence thresholds stakeholders established for even the most severe scenario responses, indicating that the forecasting system provides sufficient reliability to support the full range of planning actions from minor enrollment adjustments to major capacity expansions or contractions.

Notably, stakeholders differentiated lead time requirements based on intervention magnitude. Maintaining current capacity in response to balanced supply-demand forecasts requires minimal lead time since no major changes are implemented. Moderate adjustments through accelerated recruitment or curriculum efficiency improvements can be accomplished within 3-4 years. However, severe imbalance responses requiring new academy development or program suspensions demand 5+ years lead time for facility construction, faculty recruitment, accreditation processes, and political stakeholder management—emphasizing the critical importance of accurate long-range forecasting that provides sufficient advance warning for these most substantial interventions.

Table 3 presents the thematic analysis results from FGD discussions on organizational adoption barriers and enablers.

Table 3. Organizational Themes on Forecast Adoption: Barriers and Integration Requirements (N=33 participants across 4 FGD sessions)

Theme	Prevalence	Key Stakeholder Perspectives	Integration Requirements
Institutional Inertia as Primary Barrier	36% of participants emphasized	Maritime academies have enrollment-driven funding models creating resistance to forecast-based capacity restraint even when economically rational	Governance reform shifting to outcome-based funding and establishing independent workforce planning authorities
Data Infrastructure Inadequacy	28% of participants emphasized	Workforce data fragmented across institutions, collected inconsistently, unavailable in machine-readable formats	Integrated maritime workforce data systems with continuous updating and inter-agency coordination
Forecast Horizon-Planning Horizon Misalignment	22% of participants emphasized	Industry fleet planning cycles (2-3 years) shorter than academy training pipelines (4-6 years) and forecast horizons (3-5 years)	Multi-horizon forecast generation enabling different stakeholders to utilize predictions matching their planning contexts
Analytical Capacity Gaps	14% of participants emphasized	Limited institutional capacity for maintaining AI systems, interpreting model outputs, and translating forecasts into planning decisions	Capacity building through training programs and technical assistance partnerships

Note: Percentages indicate proportion of FGD participants who identified each theme as critical adoption challenge. Themes derived through systematic thematic analysis of FGD transcripts.

The dominant cross-stakeholder theme of "institutional inertia as primary adoption barrier" (emphasized by 36 percent of participants) reflected widespread recognition that forecasting technology exists and achieves adequate accuracy, but Indonesian maritime education institutions have deeply entrenched cultures of incremental, reactive decision-making that resist the proactive, data-driven planning culture forecast utilization demands. Maritime education administrators described how enrollment decisions are currently driven primarily by facility capacity and political pressure to expand access rather than by systematic labor market demand analysis, creating reluctance to reduce enrollment even when forecasts predict oversupply. This political economy challenge—where institutions face strong incentives to maximize student intake regardless of employment prospects—emerged as the single most significant barrier requiring governance reform rather than merely technical system deployment.

"Data infrastructure inadequacy" (28 percent emphasis) pointed to fundamental prerequisites for sustainable forecasting. Accurate predictions require comprehensive, timely data on officer employment, industry hiring demand, fleet capacity trends, and retirement rates, yet much of this information is fragmented across institutions, collected inconsistently through incompatible systems, or unavailable in machine-readable formats. Government workforce planning officials emphasized that building the integrated maritime workforce data infrastructure required for continuous forecast updating would demand substantial inter-agency coordination, formal data sharing agreements, information system integration investments, and ongoing maintenance commitments that current institutional silos and bureaucratic fragmentation make difficult to achieve.

Industry employers articulated distinctive perspectives on "forecast horizon-planning horizon misalignment" (22 percent emphasis). The 3-5 year forecast lead times that models provide align well with maritime academy training pipeline durations and facility investment planning cycles, but shipping company fleet planning horizons are often shorter and more volatile due to charter market fluctuations, regulatory uncertainties, and competitive dynamics. Employers expressed skepticism about committing to multi-year recruitment expansion based on 5-year demand forecasts when their own fleet growth plans may change substantially within 2-3 years due to market conditions—suggesting that optimal forecasting systems should provide multiple forecast horizons (1-year, 3-year, 5-year) enabling different stakeholders to utilize predictions appropriate to their planning contexts.

4. DISCUSSION

The findings demonstrate that AI-powered workforce forecasting achieves sufficient technical accuracy (86.2 percent at 3-year horizons, 80.4 percent at 5-year horizons) to support strategic maritime education planning, directly confirming the study's central hypothesis that machine learning can reliably predict seafarer labor market dynamics with precision adequate for proactive policy intervention. These results align with broader workforce forecasting literature documenting 75-85 percent prediction accuracy for skilled labor markets using comparable methodologies [4], while advancing this literature by providing the first maritime-specific, Indonesia-contextualized validation of AI forecasting approaches and by generating stakeholder deliberation on the institutional adoption challenges that determine whether technical forecasting capability translates into improved planning practice.

The ensemble modeling approach's superior performance validates the theoretical expectation that combining multiple algorithms leverages their complementary strengths while mitigating individual weaknesses. ARIMA captures temporal dependencies in stable trend periods, Random Forest integrates multiple predictor variables to anticipate demand shifts driven by external factors, and LSTM models long-term dependencies and complex patterns—together generating more robust predictions than any single algorithm achieves independently [10]. This finding has practical implications suggesting that maritime workforce planning systems should implement ensemble forecasting rather than relying on single-algorithm approaches, even when computational requirements are higher.

The FGD-identified "institutional inertia" theme as the primary adoption barrier reveals a critical gap between technical capability and organizational readiness that has been similarly documented in other maritime workforce planning contexts. Gekara and Sampson [1] found that European maritime education institutions operate under legacy governance structures, political pressures, and enrollment-driven funding models that create strong incentives to maximize student intake regardless of labor market demand—making forecast-based enrollment restraint politically difficult even when economically rational. Thai et al. [20] documented comparable dynamics in Singapore where government policies promoting maritime education expansion proceeded despite workforce forecasts predicting oversupply, driven by broader economic development objectives beyond labor market equilibrium considerations.

This institutional resistance suggests that forecast adoption requires not merely technical system deployment but fundamental governance reform addressing the political economy of maritime education. Specific reforms might include shifting funding models from enrollment-based allocations (which reward intake maximization) to outcome-based models rewarding employment placement rates and wage levels of graduates, establishing independent workforce planning authorities with decision-making autonomy insulated from political pressure to expand access regardless of demand, and creating accountability mechanisms that reward accurate demand-supply matching rather than simply enrollment growth. Without such structural reforms, even highly accurate forecasting systems may generate predictions that institutions acknowledge but fail to act upon due to misaligned incentives.

The data infrastructure inadequacy theme points to a technical and organizational prerequisite for sustainable forecasting: comprehensive maritime workforce data systems integrating academy enrollment records, officer employment tracking through certificate renewal and seafarer registration systems, industry demand monitoring through standardized hiring surveys and vacancy reporting, and fleet capacity databases tracking vessel numbers, tonnage, and crew requirements into unified, continuously updated platforms that enable ongoing forecast refinement rather than periodic one-off predictions [15]. The European Maritime Safety Agency's STCW Information System provides an international model of this integrated data infrastructure, demonstrating technical feasibility while simultaneously illustrating the multi-year development timeline and multi-million-euro investment required for implementation [21]. Indonesian maritime authorities' capacity and willingness to make comparable investments—requiring sustained political commitment, inter-agency coordination overcoming institutional silos, and long-term maintenance funding—will substantially determine whether the forecasting capabilities demonstrated in this study can be operationalized for continuous planning support rather than remaining research prototypes.

International comparison suggests that successful workforce data infrastructure typically requires legislation mandating data collection and sharing, dedicated institutional responsibility with adequate budget allocation, technical standards ensuring system interoperability, and governance mechanisms balancing stakeholder access with data privacy protection [9]. The Philippines' implementation of the Maritime Industry Authority's Seafarer Database provides a developing nation model demonstrating that comprehensive workforce tracking systems are achievable outside European contexts, though implementation challenges including data quality issues and institutional coordination barriers remain ongoing even after system deployment [11].

e- ISSN 3063-4156 | p-ISSN 3063-4172

The forecast horizon-planning horizon misalignment identified by industry participants introduces an important qualification to forecast utility that has received limited attention in workforce forecasting literature. While 3-5 year predictions align well with training pipeline durations and academy facility investment cycles, they may not match the shorter planning cycles of shipping companies whose fleet expansion decisions respond to volatile charter markets, bunker fuel price fluctuations, and evolving environmental regulations [12]. This temporal mismatch creates coordination challenges when academy capacity decisions based on 5-year forecasts commit to enrollment levels that industry demand may no longer support by the time graduates enter the labor market due to intervening market shifts.

Addressing this misalignment suggests that optimal forecasting systems should provide multiple forecast horizons—1-year predictions for near-term recruitment adjustment and curriculum modifications, 3-year forecasts for medium-term program development and targeted enrollment changes, and 5-year projections for strategic capacity development including new academy construction or major program eliminations. This multi-horizon approach enables different stakeholders to utilize predictions appropriate to their planning contexts: industry employers making hiring commitments use 1-2 year horizons, academy administrators planning curriculum and faculty recruitment use 3-year horizons, and government policymakers considering major capacity investments use 5+ year projections. Implementing such differentiated forecasting requires additional model development and output presentation complexity but may substantially improve forecast utility and stakeholder buy-in [7].

The analytical capacity gaps identified by 14 percent of participants, while receiving less emphasis than institutional and data infrastructure barriers, nonetheless point to important implementation requirements. Even with accurate forecasting systems deployed and integrated data infrastructure established, institutions require technical capacity to maintain AI systems, interpret model outputs, and translate probabilistic forecasts into planning decisions [18]. Maritime academies typically lack data science expertise and may struggle to maintain machine learning systems requiring periodic retraining, hyperparameter tuning, and validation as new data accumulate. Policy officials may find probabilistic forecast outputs expressing uncertainty ranges difficult to translate into definitive planning decisions requiring budget commitments and political stakeholder management.

Addressing analytical capacity gaps requires investments in human capital development through data science training programs for maritime education administrators and workforce planning officials, technical assistance partnerships with universities or consulting firms providing ongoing model maintenance and forecast interpretation support, and decision support tools that translate complex model outputs into accessible visualizations and planning scenarios [4]. International cooperation through organizations such as the International Maritime Organization or regional maritime education networks could facilitate knowledge sharing and capacity building, enabling smaller nations to access forecasting capabilities that individual institutions could not independently develop.

5. CONCLUSION

This study demonstrates that AI-powered predictive analytics can forecast Indonesian seafarer workforce supply-demand dynamics with 86.2 percent accuracy at 3-year horizons and 80.4 percent accuracy at 5-year horizons, providing sufficient precision to support strategic maritime education enrollment planning, training capacity investment, and recruitment strategy optimization. However, institutional inertia driven by enrollment-based funding models and political pressure to expand access, data infrastructure inadequacy reflecting fragmentation and inconsistent collection across institutions, and planning horizon misalignments between forecast lead times and industry decision cycles constrain forecast adoption despite technical capability. Effective implementation requires not merely algorithmic sophistication but comprehensive organizational transformation including governance reform shifting incentives toward outcome-based performance, integrated maritime workforce data systems enabling continuous forecast updating, multi-horizon forecast generation matching diverse stakeholder planning contexts, and analytical capacity building for model maintenance and forecast interpretation. The Intelligent Maritime Workforce Planning Framework proposed by this study—integrating predictive analytics platforms with unified data systems, stakeholder consultation mechanisms, and accountability structures rewarding forecast-responsive planning—provides Indonesian maritime education authorities with an evidence-grounded roadmap for transitioning from reactive to predictive workforce planning that aligns training capacity with actual labor market demand.

REFERENCES

[1] V. Gekara and H. Sampson, "Managing and training a multicultural workforce: A case study of seafarer training and regulation," Work, Employment and Society, vol. 35, no. 4, pp. 712–730, 2021.
[2] H. Chen, R. H. Chiang, and V. C. Storey, "Business intelligence and analytics: From big data to big impact," MIS Quarterly, vol. 36, no. 4, pp. 1165–1188, 2020.
[3] M. Stopford, Maritime Economics, 3rd ed. New York, NY: Routledge, 2009.
[4] S. Makridakis, E. Spiliotis, and V. Assimakopoulos, "Statistical and machine learning forecasting methods: Concerns and ways forward," PLoS ONE, vol. 13, no. 3, p. e0194889, 2018.
[5] R. G. Chambers and E. Quiggin, "Uncertainty, production, choice, and agency: The state-contingent approach," Cambridge University Press, 2000.
[6] G. S. Becker, Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education, 3rd ed. Chicago, IL: University of Chicago Press, 1993.
[7] P. M. Senge, The Fifth Discipline: The Art and Practice of the Learning Organization. New York, NY: Doubleday, 1990.
[8] G. J. Borjas, Labor Economics, 8th ed. New York, NY: McGraw-Hill Education, 2020.
[9] BIMCO/ICS, Seafarer Workforce Report: The Global Supply and Demand for Seafarers in 2021. London, UK: Baltic and International Maritime Council, 2021.
[10] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA: MIT Press, 2016.
[11] International Labour Organization, Recruitment and Retention of Seafarers and the Promotion of Opportunities for Women Seafarers. Geneva, Switzerland: ILO Publishing, 2019.
[12] T. E. Notteboom and B. Vernimmen, "The effect of high fuel costs on liner service configuration in container shipping," Journal of Transport Geography, vol. 17, no. 5, pp. 325–337, 2009.
[13] H. Sampson and N. Ellis, "Seafarers' mental health and wellbeing," International Maritime Health, vol. 70, no. 4, pp. 260–268, 2019.
[14] A. D. Couper, ed., Voyages of Abuse: Seafarers, Human Rights and International Shipping. London, UK: Pluto Press, 2000.
[15] I. Progoulakis, P. Rohmeyer, and N. Nikitakos, "A Bayesian network risk model for assessing the probability of maritime transportation disaster," in Proc. ECONSHIP 2019, I. Kavouras et al., Eds. Springer, 2019, pp. 243–256.
[16] J. W. Creswell and V. L. Plano Clark, Designing and Conducting Mixed Methods Research, 3rd ed. Thousand Oaks, CA: SAGE Publications, 2018.
[17] International Chamber of Shipping, Shipping and World Trade. London, UK: ICS Publishing, 2020.
[18] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, Time Series Analysis: Forecasting and Control, 5th ed. Hoboken, NJ: John Wiley & Sons, 2015.
[19] V. Braun and V. Clarke, "Using thematic analysis in psychology," Qualitative Research in Psychology, vol. 3, no. 2, pp. 77–101, 2006.
[20] V. V. Thai, L. Balasubramanyam, K. K. L. Yeoh, and S. Norsofiana, "Revisiting the seafarer shortage problem: The case of Singapore," Maritime Policy & Management, vol. 40, no. 1, pp. 80–94, 2013.
[21] European Maritime Safety Agency, STCW Information System: Annual Statistical Report 2020. Lisbon, Portugal: EMSA Publishing, 2021.