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A Smart Maritime HR Analytics Framework for Talent Forecasting and Operational Efficiency

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ABSTRACT

The maritime sector is going through a dynamic change, shaped by globalization, digitalization and changing operational requirements that result in major challenges in workforce planning, retaining talent and aligning skills. Maritime organizations face challenges with traditional HRM practices, such as reactive decision-making, which prevent them from predicting manpower shortages, optimizing crew deployment, and improving individual employee performance in dynamic operations. Random Forest Algorithm for talent forecasting, attrition prediction, performance prediction and Genetic Algorithm for workforce allocation and crew optimization. The proposed model brings together and combines various HR and operations data sources, such as employee competencies, performance records, training logs, employee attrition metrics, competency maps, employee schedules, and operational workload metrics, to create actionable human resource intelligence. These include advanced analytical tools like machine learning powered forecasting, workforce segmentation, predictive attrition modelling, and optimization algorithms, enhancing talent acquisition planning, anticipating skill shortages, and enabling efficient workforce deployment in maritime operations. The framework is also built around the concept of adaptive decision support which enables the organizations to align their human capital strategies to operational requirements, safety requirements and organizational sustainability. In conclusion, the proposed framework offers a comprehensive and structured solution that integrates predictive talent analytics with operational optimization, empowering maritime organizations to optimize productivity, reduce employee disruptions, streamline retention efforts, and enhance operational resilience. Moreover, the framework also enables informed management decisions based on real-time analysis, thus helping to create a more agile, efficient and sustainable maritime workforce ecosystem. The study provides a conceptual framework for maritime HRM systems that the potential of AI-driven analytics to impact the future of workforce management and operational efficiency in the maritime industry.The research also sets the stage for intelligent maritime HRM systems and emphasizes the importance of AI-powered analytics in shaping the future of maritime workforce management and operational efficiency.

1. Introduction.

The maritime industry is vital to international trade and is a key enabler within the global economy for the transportation of goods, energy supplies and commodities between countries and regions. With the constant evolution of maritime operations with respect to technological progress, complexity of the rules, increasing competition, etc., human capital has become a priority for the maritime organizations labi, K.O. (2024). Empowerment of the workforce, availability of crew members and development and retention of special skills have been recognized as important aspects that influence the performance, safety and sustainability of any organisation. However, the traditional human resource practices in the shipping sector are still largely

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reactive and administrative, and there are still few forecasting tools to explain the needs of the workforce and how best they can be utilised in a dynamic operational context Sánchez et al., (2022).

The special nature of maritime employment is that it is global, is based on rotational arrangements, features multi - component crews, is physically intensive and has high requirements for certification. This results in ongoing issues like skill shortages, high turnover, fatigue, competency mismatch and poor crew deployment Shanti Devi and Deepesh Ranabhat (2023). In addition, the digitalisation of shipping operations has led to a growing need for digital data-driven strategies for workforce that can meet the evolving requirements of the operations. As data accumulation in the maritime sector continues to rise, organisations are presented with a greater chance of using Artificial Intelligence, predictive analysis and intelligent decision support systems in their human resource management systems to make the systems proactive, instead of reactive, which enhances decision making Gurusinghe et al., (2021). The maritime industry generates increasing amounts of data about employees, operations, and performance, and companies have more opportunities than ever to leverage AI, predictive analysis, and intelligent decision support systems to make their human resources management systems more proactive than reactive, to optimize decision making.

In this regard, the idea of smart HR analytics has become a good option for workforce planning and operational optimization Mohammed Ali Aldossary and Jamshid Pardaev (2025). Advanced analytical tools can combine historical records of workers, competencies, learning experiences, retention rates, schedules, and metrics to provide valuable insights for anticipating future talent needs, addressing new competencies, forecasting employee turnover, and optimizing staffing utilization Nazmus Sakib et al., (2024). Maritime organizations can leverage machine learning models, optimization algorithms, and real-time analytical dashboards to complement strategic decisions, enabling them to allocate human resources more effectively while ensuring operational continuity, safety, and employee well-being.

This research proposes a conceptual and analytical framework for Talent Forecasting and Operational Efficiency to enhance the intelligence of workforce in a maritime organization John, A.S. and Hajam (2024). It is envisioned that the proposed framework will enable to link predictive talent analytics, operational workforce optimization and strategic human capital planning into one intelligent system which will provide support to adaptive, evidence-based HR decision making. The study not only tackles the challenge of understanding talent but also provides a vision for the future of maritime human resource management (HRM) – a system that is smarter, more agile, and sustainable – highlighting the impact of AI-powered analytics on the future of maritime HRM Kamaruzzaman and Kamaruzzaman Z.A (2025).

2. Research Objetive.

The main goal of this study is to create a smart maritime HR analytics framework based on machine learning to enhance talent forecasting and aid in maritime workforce planning. Specific goals are to:

1. To create an integrated maritime HR analytics framework that combines all HR data on employees in a single data repository to support HR analysis of the workforce.
2. To create a Predictive Workforce Model using the Random Forest approach to predict workforce needs, skill gaps and support talent management by precise prediction of employee potential and future workforce needs.
3. To understand the main factors that affect employee performance, competency and retention in the workforce by performing the Feature importance analysis to support evidence-based HR decision making.
4. To assess the performance of the proposed framework with the typical performance metrics of machine learning such as Accuracy, Precision, Recall, F1-score, Confusion Matrix and ROC-AUC and demonstrate its applicability in maritime organizations for strategic workforce planning.

3. Related Work.

Hamid et al., (2025) in [9] underlines the importance of human resource analytics in making informed decisions based on data to improve the performance of the human resources, increase employee productivity and retention and consequently the performance of the organization. The research revealed that HR analytics has a strong connection to strategic decision-making, which has a positive impact on productivity, retention, and organizational efficiency, when used in the areas of recruitment, training and development, and employee engagement. The results also highlight the role of AI powered digital technologies in fostering these relationships, enhancing HR systems' intelligence and effectiveness. Furthermore, indirect analysis showed that the positive impact of HR analytics on employee outcomes is mainly through the enhancement of the managerial decision making process. Overall, the study highlights the potential of predictive HR analytics when applied with advanced digital technologies as a comprehensive solution for optimized workforce management, better employee performance, and sustainable competitive advantage.

Autsadee, Y et al., (2024) in [10] explores the rising influence of digitalisation in the Human Resource Development (HRD) of the maritime industry and its contribution to the competitiveness of an organisation. The study employs a detailed bibliometric framework to explore the impact of digital transformation on essential HR areas like workforce management, training and development, performance management, employee experience, and HR strategy alignment in maritime companies. The results highlight the importance of implementing digital HRD practices to boost the efficiency of operations, optimize the performance of the workforce, and ensure a better synergy between HRD and the broader organizational goals. The research also underscores the burgeoning promise of Artificial Intelligence based on digital HR systems in terms of revolutionizing HR practices in the maritime industry and enhancing competitive edge through technology.

Using quantitative predictive modeling and qualitative stakeholder analysis, Literasisains et al., (2026) in [11] discusses the implementation of an Artificial Intelligence system for forecasting maritime education workforce, which involves developing predictive models. Advanced forecasting models like ARIMA, Random Forest regression and LSTM neural networks were applied using historical workforce data to make forecasts of seafarer supply-demand levels with high forecasting accuracy. The results indicate that AI-driven ensemble models are good predictors of workforce gaps for long-term strategic planning and can be used to match the output of maritime education and industry workforce need. But factors like data infrastructure, institutional resistance, and planning misalignment are major obstacles for effective adoption. The study proposes an intelligent maritime workforce planning framework, that includes predictive analysis, the maritime workforce including a single source of truth and a structured decisionmaking process to support maritime HRP and policy development.

Progoulaki, M. and Theotokas, I (2016) [12] point out that human resource management and cultural diversity management are important strategic elements of the shipping industry that help an organization become competitive. The study combines the resource-based view and human resource/cultural diversity management theories to suggest a framework for managing culturally diverse maritime workforces. The study highlights the need for effective crew management: the coordination, engagement and competency of the crew are key capacities in maritime human resources. It finds that the management of human capital and cultural diversity can provide sustainable competitive advantage and better long-term operation performance to companies in the shipping industry.

This study, conducted by Zou, Y., Xiao, G., Li, Q. and Biancardo, S.A et al., (2025) [13] explores the integration of Artificial Intelligence, IoT, and port automation in the evolution of sustainable maritime intelligence and how these technologies are increasingly shaping the efficiency and management of carbon emissions in port operations. The results highlight the significant technological advancement in the development of smart maritime systems, including the technologies of digital twin ports, intelligent decision-making models, and other related functions, that can enhance energy efficiencies and cut down on operational delays. There are gaps to be addressed in field of cross-system standardisation, climate adaptive modelling, regulatory harmonisation, and international cooperation. The study suggests a technological and governance approach to facilitate integration and cross-referencing of maritime data from several sources and to advance more intelligent policy coordination and sustainable digital transformation in global maritime ecosystems.

The skills and competencies needed for future autonomous shipping are summarized in [14] by Belabyad et al., (2025) which offers an extensive review. The results reveal a comprehensive competency framework which comprises technical / digital competencies, operational/managerial competencies, critical thinking, problem-solving, and interpersonal competencies required for the operation/s of autonomous ships. The study highlights the need for modernizing marine education and training via a blended learning method that encompasses the knowledge acquired at sea and the new digital skills acquired through technology. It also highlights the importance of lifelong learning, flexibility and team working for workforce development and successful transition to smart and autonomous ships.

Wang, L. and Hsu, H.-H et al., (2025) [15] discussed the use of the Internet of Things (IoT) in the field of maritime logistics. It focuses on the potential benefits of IoT in realtime tracking, monitoring and intelligent control systems within maritime logistics operations. The study provides the fundamental knowledge of the IoT architecture, comprising perception, network and application layers, as well as relevant standards and communication protocols used for maritime digital infrastructure. It also highlights the significance of data collection, pre-processing, cleansing, standardization and analytical approaches using the Internet of Things for improving logistics operations like routing, scheduling, stock management and monitoring. The findings show that by leveraging IoT and data analytics, marine transport can significantly enhance its efficiency, cost-effectiveness, service quality, and intelligent decision - making process, ultimately supporting maritime logistics management in the digital transformation.

4. Methods.

The research for this study suggests a Framework for Talent Forecasting and Operational Efficiency which is an intelligent human resource management model that will enable the transformation of the traditional HRM system in the maritime industry to a proactive, predictive and data-driven approach. The framework is designed to tackle some of the key issues within the maritime industry that encompass skills gaps, skills shortages, loss of crew, fatigue, sub-optimal use of resources and inadequate skills development Noto, S et al., (2023). The proposed model will include the advanced analysis tools and the operational workforce intelligence to support better decision-making for TA, retention planning, crew allocation and long-term workforce optimization.

The framework is proposed to have five interconnected layers data acquisition, data preprocessing and integration, predictive analytics, workforce optimization, and intelligent decision support. Data for the workforce is gathered in various workforce-related data sources such as employee demographic information, education and qualification data, certification or qualification data, competency data, training outcomes, job performance data, attendance data, promotion data, attrition data, voyage data, operational workload data, and safety compliance data Liu, Q. (2024) during the data acquisition stage. This multi-dimensional dataset is the foundation to more in-depth workforce intelligence modelling.

The captured data is then cleaned, normalized and processed for missing values, feature extraction and structured analytical format during preprocessing and integration. These workforce indicators are derived using feature engineering techniques, such as calculating the retention probability, performance trends, competency alignment, and the likelihood of fatigue, workforce utilization rate, and future staffing demand. Data integration mechanisms are then used to integrate HR and operational data and create a single repository of maritime workforce intelligence.

The predictive analytics layer employs ML algorithms to forecast the requirements for the workforce and analyse workforce outcomes. Random Forest models, Support Vector Machine and Gradient Boosting models predict the risk of attrition, the likelihood of retention and training needs. The future demand for manpower is estimated using regression model and time-series forecasting model, and skill shortages and the distribution of the manpower resources in the various maritime operations are also estimated. The employee segmentation is further done using clustering techniques to provide competencies, experience and performance-based segments that can be used for targeted workforce planning.

For optimizing operational efficiency, the workforce optimization layer (WOL) involves the use of metaheuristic and mathematical optimization methods, including genetic algorithms (GA), particle swarm optimization (PSO), and linear programming (LP), which can be used to optimize crew deployment, role matching, training scheduling, and workforce balancing Zhou et al., (2024). Multi-objective optimization is implemented to achieve multiple objectives: maximise productivity, engagement of employees, utilisation of resources; simultaneously minimise workforce shortage, employee turnover, operational disruption.

The last part is the creation of an intelligent decision-support layer, which shows predictive insights through analytical dashboards and recommendation systems. This module can give HR managers and maritime operational planners actionable information about recruitment planning, succession management, development of skills priorities, retention intervention and optimized allocation of the workforce Cao H et al., (2024). The Figure 1 shows the work flow of proposed work.

4.1. Data Collection.

The proposed framework started with the collection of maritime HR and operational data across various sources to form a comprehensive maritime human resource data set. Demographic data of employees, crew competencies, employee certification records, years of maritime experience, marine training logs, performance and attendance logs, leave history, voyage assignments, safety compliance logs, and employee attrition history were all gathered. These variables provided a comprehensive description of the workforce and provided predictive analysis of future workforce needs.

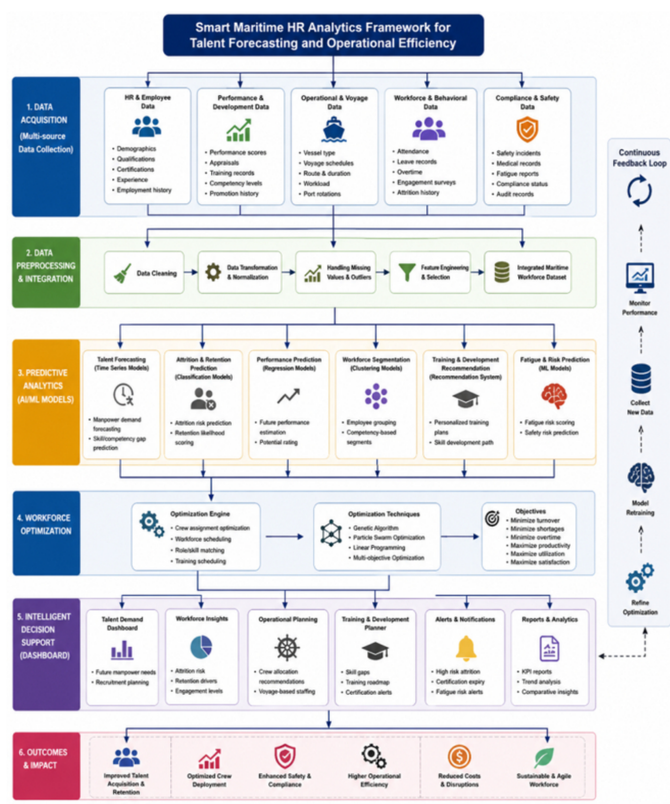
Primary data collection was done using a structured survey methodology with maritime practitioners. A questionnaire was sent to 300 respondents, which consisted of 80 deck crew, 60 marine engineers, 50 senior officers, 30 HR managers, 30 operations managers, 25 training officers and 25 safety compliance officers. Stratified random sampling was employed to obtain a reasonably good representation, by occupational groups and by work experience levels.

Data was gathered from the 45 questions across eight dimensions: (i) demographic information, (ii) professional competency, (iii) job performance, (iv) employee well-being/fatigue, (v) retention intention, (vi) training and professional development, (vii) operational working conditions and (viii) organizational engagement. A five-point Likert scale was used for the responses, with a binary (Yes/No) and numerical response field, as appropriate. Of this, some 13,500 data records were generated as an individual result of the completed survey, and thus became the data for further analysis.

A pilot study was done with 30 respondents to test the reliability and understanding of the questionnaire before the main study. Cronbach's alpha was used to test the reliability of the survey instrument and the questionnaire was modified as a result of feedback from the participants before the start of the data collection.

After collecting the data, the data was preprocessed by removing duplicates, filling missing values, encoding categories, normalizing features and creating new features (feature engineering). The processed dataset was fed into a predictive analytics model using Random Forest to facilitate talent forecasting, workforce demand forecasting, skill gap identification and strategic planning of the maritime workforce.

Figure 1: Work Flow of Proposed Work.



Source: Authors.

4.2. Data Pre-Processing and Integration.

The data pre-processing and integration is an important step for the proposed work since the digital data collected through surveys and data operationalized in HRs may have missing values, inconsistent formats, duplicate information, categorical responses, different scales of measure. This part aims to transform raw maritime HR data into a machine-learning ready, clean, and structured dataset. This stage is performed using a Structured Data Cleaning, Encoding, Normalization and Feature Integration Methodology.

The first step is reviewing the survey data after a collection of data from maritime professionals has taken place. The survey can range from 300 respondents and have 40-50 variables that can include age, experience, designation, skill score, training status, fatigue level, satisfaction level, intent to remain, certification status, performance indicators, etc. Every answer is evaluated for completeness, validity and appropriateness for analytical purposes.

i. Missing Value Handling.
Survey responses may not be complete, and may be missing. Appropriate data handling for missing data is used. If there are missing values for numerical variables, e.g. age, experience, work hours, performance score, the mean or median value can be used to replace the missing values. If there are missing values for categorical data variables, they may be imputed with the mode value of the variable. It is possible that a response may have a lot of missing answers, such as over 30% of the answers, and that response can be eliminated from the data set.

ii. Duplicate Record Removal.
The possibility of duplicate entries will arise if a participant fills out the survey more than once. These duplicate records are matched by their employee id, email id, designation or response time stamp. Only one record will be kept and multiple entries will be removed to prevent skewed results.

iii. Data Cleaning.
At data cleaning stage, survey responses that are inconsistent, incomplete, and unstructured are transformed to a consistent and uniform analytical format to enhance the quality of the data and the reliability of the model. Job titles such as "Marine Engg." are standardized to "Marine Engineer"; and longer designations like "Deck Crew Member" are shortened to "Deck Crew" for consistency in using the categories. For consistency with binary responses, answer items like "Yes " are corrected to "Yes". Entries with no value or not available are considered missing and are dealt with using proper imputation techniques. Likewise, numerical answers in text form, e.g., "5 years", are converted to numbers (5) for statistical analysis and machine learning processing. This standardisation process enables raw data from the maritime workforce survey to be cleansed, consistent and organised for meaningful predictive analysis and workforce optimisation. Table 1 lists the sample Dataset that were collected and used for this analysis.

iv. Normalization.
Survey data has variables that are measured on various scales. For instance, age can be between 20 and 60, the performance score from 0 to 100, and fatigue level can be from 1 to 5. Normalization is performed to prevent the domination of large scale variables. Min-Max Normalization is an appropriate technique.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Table 1: Sample Dataset.

Employee_ID	Experience	Skill_Score	Fatigue_Index	Satisfaction	Training Need	Attrition Risk	Performance
E001	8	4.5	0.30	4	0	Low	High
E002	3	3.2	0.80	2	1	High	Medium
E003	10	4.8	0.20	5	0	Low	High

Source: Authors.

4.3. *Feature Engineering.*

Feature engineering is the process of adding relevant data from maritime HR surveys to an indicator of the workforce to improve the accuracy of a model and/or optimization tool. In the proposed work, feature engineering is applied to the data collected from employee feedback, HR records, and operational data, to convert them into structured variables that can be used for talent forecasting, attrition prediction, performance analysis, and crew allocation.

The Weighted Composite Feature Engineering Method is appropriate for this study. These are indicators supporting decision making such as Skill Gap Score, Fatigue Risk Index, Retention Score, Training Need Score, and Workforce Utilization Rate, which are derived in this way by combining multiple related indicators with assigned weights. The summarization of the methods employed to feature engineering in the proposed work is presented in Table 2.

Table 2: Summarization of Feature Engineering.

Engineered Feature	Method	Purpose	Expected Outcome
Skill Gap Score	Required Skill Level − Current Skill Level	Measures difference between expected competency and existing employee skill	Identifies employees needing upskilling/reskilling
Fatigue Risk Index	Weighted score using work hours, stress, voyage duration, physical exhaustion, and sleep quality	Evaluates workforce fatigue and burnout risk	Improves crew welfare planning and reduces fatigue-related operational risks
Retention Score	Weighted combination of job satisfaction, salary satisfaction, career growth, organizational support, and work-life balance	Predicts employee retention likelihood	Supports attrition prevention and retention strategy development
Training Need Score	Composite score using skill gap, certification expiry, low performance, and digital competency gap	Determines urgency and priority for employee training	Enables targeted training recommendations and skill enhancement
Workforce Utilization Rate	(Actual Working Hours / Available Working Hours) × 100	Measures workforce allocation efficiency	Helps balance workload and optimize resource utilization

Source: Authors.

4.4. *Talent Forecasting Using Random Forest.*

The most important predictive model in the proposed Smart Maritime HR Analytics Framework is the Random Forest (RF) model, which is used to forecast future skills and needs of the workforce, identify employees who are at risk of leaving, predict skills gaps, predict training requirements based on past and present workforce data, etc. Random Forest is an ensemble learning technique that is based on the aggregation of different decision trees to get more accurate predictions, less variance, and stable predictions in a complex workforce data. Maritime HR data is inherently multidimensional and presents both numerical and categorical variables, which have often non-linear relationships, with no apparent reason to make some strong statistical assumptions when modelling the behaviour of workforce. And another reason why RF is suitable for the problem.

The idea behind RF is that many decision trees are used separately to make predictions and then the predictions of all the decision trees are aggregated to produce the final prediction. RF is not formed from a single decision tree that might overfit the training data, but rather a collection of many decision trees built with random subsets of workforce records and random subsets of the predictor features. There are multiple trees that have learned different patterns on the maritime HR dataset, and thus the overall model is more stable and generalized. For classification problem like attrition prediction (Stay/Leave) the output is obtained by majority voting and for regression problem like manpower demand forecasting the output is obtained by averaging all the outputs from all the trees.

Talent forecasting is based on a number of engine variables, such as Skill Gap Score, Fatigue Risk Index, Retention Score, Training Need Score, Workforce Utilization Rate, Performance Efficiency Score, Certification Validity Score, Experience Level, Operational Workload and Voyage Intensity Index. They are a measure of the skills of staff, the intensity of the operations and the productivity and stability of staff. The target variable can be based on the forecasting objective such as Future Talent Requirement (Low/Moderate/High), Attrition Risk (Yes/No), Promotion Readiness or Training Priority Level. The association between these input indicators and the HR outcome is then employed to train the Random Forest model, which can then be used to make predictions about the HR outcome in the future.

Algorithm 1: Random Forest for Talent Acquisition.
Input: Maritime HR dataset D.
Output: Talent prediction result.
Step 1: Load dataset D.
Step 2: Preprocess D.
Remove duplicate records.
Handle missing values.
Normalize numerical features.
Step 3: Select important features F.
F = {Age, Experience, Training Score, Certification, Performance Rating, Sea Service Years, Skill Level}
Step 4: Encode categorical attributes into numerical form.
Step 5: Split D into training set and testing set
Train_Set = 80%.
Test_Set = 20%.
Step 6: Initialize Random Forest model RFSet number of decision trees N = 100.
Step 7: For each tree Ti in RF:Select random sample from Train_Set.
Select random subset of features.
Build decision tree Ti.
Step 8: For each test record X:
Get prediction from each tree Ti.
Final prediction = majority voting.
Step 9: Evaluate model using accuracy, precision, recall, and F1-score.
Step 10: Return predicted talent category.

4.5. Workforce Optimization Using Genetic Algorithm.

A Genetic Algorithm (GA) is an optimization technique that is based on the process of natural selection. This method creates several possible workforce allocations and iterates them to gradually improve over time. All the possible solutions are viewed as a "chromosome." The best solutions are chosen, assembled and adjusted to get an optimal or near-optimal workforce plan.

The main purpose of GA is to place the person in the right job, ship, trip and timetable and ensure that they are able to meet the requirements of maritime operations, such as certification validity, crew availability, skill level, workload balance, safety compliance, etc. and cost efficiency. Table 3 shows the sample output after the validation.

Step 1: Define Optimization Objective.
The first step is to specify the optimization goal for the GA. Maximize Skill-Role Matching, Minimize Workforce shortage, Minimize Fatigue risk, Minimize Operating cost etc.
Step 2: Define Input Variables.
Decision-making information for the GA are processed HR and operation data. Unique identity of each employee, Employee's competency level, Validity of required maritime certificates, Years of maritime service, Whether employee is available for assignment, Fatigue level predicted from work patterns, Employee stability indicator, Required crew count and role, Length of assigned voyage, Expected operational pressure and Salary, overtime and deployment cost.
Step 3: Chromosome Representation.
A Chromosome is a complete workforce allocation plan in GA. The employees are assigned to the needed roles, each of which is represented by one gene in the chromosome.
Step 4: Initial Population Generation.
The algorithm generates initial set of possible crew allocation solutions at random.
Step 5: Fitness Function Design.
The fitness function shows how well each workforce allocation solution does. The more fit the crew allocation plan, the higher its fitness value.
Step 6: Constraint Checking.
For each solution, maritime workforce constraints are checked.
Step 7: Selection.
Selection is the process of the best solutions from the population for further reproduction.
Step 8: Crossover.
Crossover is a unification of 2 good workforce allocation solutions to provide new solutions.
Step 9: Mutation.
Mutation changes the solution by randomizing a part of it to ensure diversity and not being trapped in a local optimum.

Step 10: New Population Formation.

A new generation of workforce allocation solutions is created after selection, crossover and mutation. Elitism, the direct selection of top performing solutions to directly pass on to next generation, might be the best solution to be preserved. This will ensure that good allocation plans are not wasted.

Step 11: Termination Condition.

The algorithm is repeated until a stopping criterion is attained.

Step 12: Final Optimized Workforce Plan.

The optimized workforce allocation plan is the best solution from the last generation.

Table 3: Example Output after Validation.

Role	Skill	Employee	Skill Score	Fatigue Risk	Certification	Status
Marine Engineer	5	E012	5	Low	Valid	Suitable
Deck Officer	4	E025	4	Medium	Valid	Suitable
Safety Officer	5	E041	5	Low	Valid	Suitable
Crew Member	3	E088	4	Low	Valid	Suitable

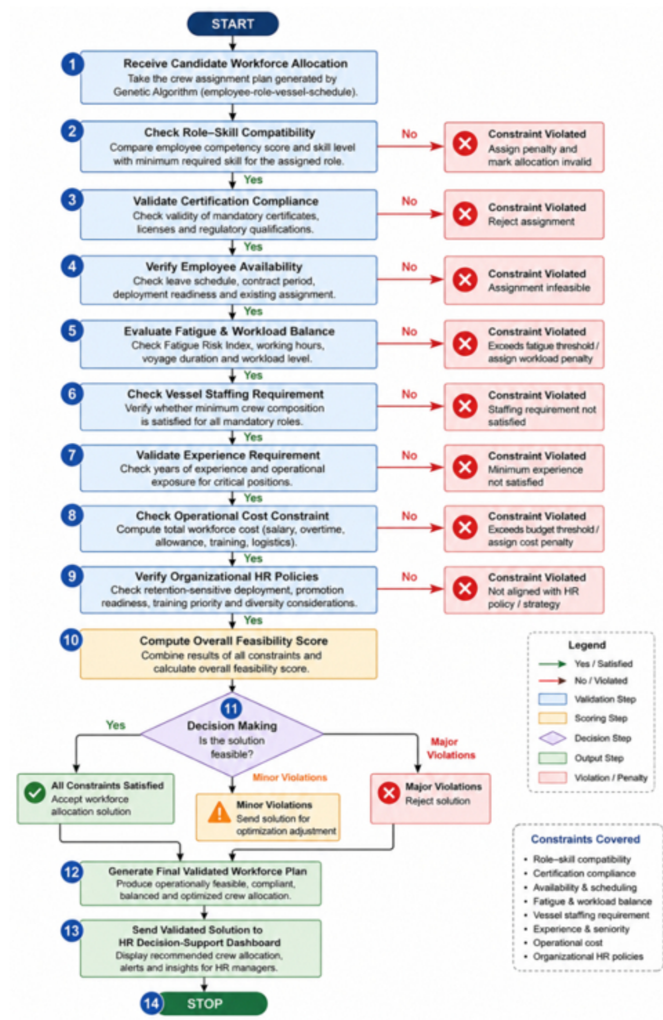
Source: Authors.

In the proposed work, the GA is used as an optimization engine which translates the prediction results into real workforce decisions. It considers several crew allocation scenarios, determines the optimal crew allocations, performs crossover and mutation, analyzes operational constraints, and generates an optimized maritime crew plan. This will enable maritime institutions to optimize deployment of their staff, increase employee productivity, prevent staff shortages, manage operational costs and mitigate fatigue.

4.6. Constraint Checking.

The proposed Smart Maritime HR Analytics Framework encompasses a set of constraints that are checked during the workforce optimization phase to ensure all crew allocation solutions provided by the Genetic Algorithm are feasible, compliant and operationally efficient. Optimization algorithms can yield many combinations of how a workforce can be allocated, but not all combinations are feasible for maritime operations due to the regulations, operations, technical and human resources conditions. Therefore, constraint checking acts as a filter and validation process that verifies that any allocation of maritime workforces complies with pre-established maritime workforce rules before it can be an optimal deployment plan. This work constraint checking is proposed as an multi-constraint feasibility evaluation model that considers and systematically evaluates each workforce assignment generated for competency alignment, certification compliance, operational readiness, workload balance, safety requirements and organizational policy limits. This enables the mathematically optimum scheduling of crew crews to be realised and is now deployable in maritime operational environments. The proposed work involves step by step process of constraint checking is explained in Figure 2.

Figure 2: Step by Step Procedure of Constraint Checking.



Source: Authors.

4.7. Decision Support Dashboard.

The Decision Support Dashboard includes the final intelligence layer in the proposed Smart Maritime HR Analytics Framework for Talent Forecasting and Operational Efficiency, to help translate predictive analytics and HR optimization into managerial insights that can be acted upon. After creating talent forecasts using the Random Forest model and generating optimized crew allocation solutions with the Genetic Algorithm, the dashboard is intended to be a single, integrated visualization and decision-making tool for maritime HR managers, fleet supervisors, operational planners and executive management. The dashboard offers a real-time, centralized, and analytical perspective on workforce health, readiness, and future talent needs, as opposed to traditional reactive workforce planning and manual reporting.

Talent Demand Forecasting Panel.

- Forecasts future workforce needs in the context of vessel operations, voyage planning, departmental requirements and competency demand.

- Assists in the hiring process by helping decide the required hiring needs and assist in planning for them in advance.

Attrition Risk Monitoring Panel.

- Identifies staff members at risk of leaving using retention score, fatigue, job satisfaction and career development metrics.
- Identifies employees as being low, medium, or high risk for attrition and implements retention strategies as needed.

Skill Gap and Training Recommendation Panel.

- Determines the competencies needed in the workforce, the renewal of certification needs, and the need for technical upskilling.
- Gives tailored training suggestions and abilities development notifications.

Crew Allocation and Operational Planning Panel.

- Shows ideal employee-to-role mapping, vessel crew scheduling and workload allocation.
- Ensures efficient crew deployment and minimises operational crew risk.

Fatigue and Workforce Wellness Monitoring Panel.

- Ensures employee fatigue, hours logged, stress indicators, well-being scores are being monitored.
- Helps create a safer schedule, workload distribution and a prevention of burnout.

Compliance and Certification Monitoring Panel.

- Monitors validity of certifications, requirements for training and compliance deficiencies.
- Alerts on upcoming certification and incomplete qualification.

Management Analytics and KPI Panel.

- Assesses workforce productivity, retention, absenteeism, utilization, compliance and efficiency.
- Supports leadership in tracking HR performance by analyzing trends and reporting on key performance indicators (KPIs).

Intelligent Alert and Recommendation Engine.

- Recognizing critical workforce issues such as manpower shortage, high employee turnover, fatigue overload and talent deficiency.
- Proposes remedial measures such as recruitment and training, job rotations, scheduling.

Unified Decision-Making Platform.

- Combines predictive analytics, optimization outputs, employee wellness, compliance monitoring and HR strategy into a single dashboard.
- Allows for workforce planning and operational decisions made in real time, based on data.

5. Analysis & Results.

Evaluation of the performance is a step in the proposed Smart Maritime HR Analytics Framework for Talent Forecasting and Operational Efficiency, which entails a systematic testing of the effectiveness, accuracy, reliability and usefulness of the built and developed models in the previous steps. Evaluation is not about the power of a predictive model; it's about making sure the model is helping to make HR workforce planning, crew deployment, employee retention, compliance readiness and operational productivity better in the real world of maritime HR.

i. Evaluation of Predictive Model Performance (Random Forest).

The first level of evaluation is on the Random Forest forecasting model for workforce demand, attrition risk, skill shortage and training needs. Ten-fold cross validation is recommended for the robustness and to reduce the bias, the preprocessed maritime HR data can be split into training data and testing data, with 80% and 20% respectively. The forecasting model is evaluated with classification and regression metrics for various forecasting tasks.

The following measures are used for classification tasks like classification of attrition, talent demand classification and training requirement classification:

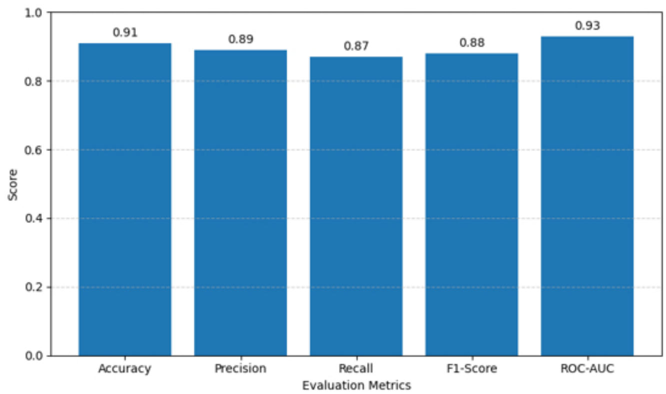
i. Accuracy-This provides a measure of how accurate the predictions made by the model are (percentage of correct predictions).
ii. Precision – percentage of true positive predictions when making a prediction of positive outcomes.
iii. Sensitivity – percentage of those who are truly positive who are detected as positive
iv. F1-score – harmonic mean of precision and recall
v. ROC-AUC score – ability of the model to distinguish between classes

Table 4: Performance Analysis.

Metric	Score
Accuracy	0.91
Precision	0.89
Recall	0.87
F1-Score	0.88
ROC-AUC	0.93

Source: Authors.

Figure 3: Performance Analysis.



Source: Authors.

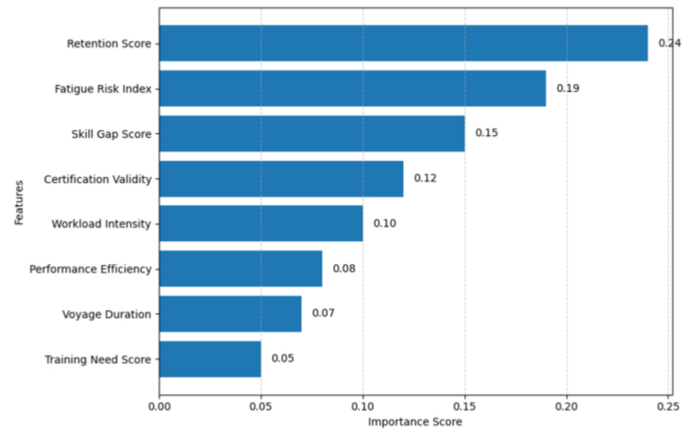
Table 4 and Figure 3 of the performance evaluation of the Random Forest model demonstrate that the model has a very good predictive capability in the framework proposed for maritime talent forecasting. The model is reliable in predicting workforce needs and the need for training (91% accuracy, 89% precision, 87% recall, 88% F1-score, 93% ROC-AUC score), as well as the risk of staff turnover (93% accuracy, 89% precision, 87% recall, 88% F1-score, 93% ROC-AUC score). The findings show that the model is able to accurately identify patterns of workforce and to effectively categorise the employees into various risk groups and gives stable prediction performance with a minimum number of false alarms. Overall, the performance of the Random Forest is good with respect to the workforce knowledge and it can be considered as a good predictive model for strategic maritime human resource planning and operational decision making.

ii. Feature Importance Evaluation

The importance of indicators produced by the proposed framework should be evaluated; feature engineering is an important part. An advantage of Random Forest is the feature ranking scores that determine which of the variables is most important in predicting results.

The key features assessed in workforce analysis encompass the Retention Score, which indicates the probability of retaining employees; the Fatigue Risk Index, which gauges an employee's potential fatigue or burnout; the Skill Gap Score, which identifies skill deficits between the employee and the job; Certification Validity Score, which assesses the validity and relevance of the employee's certifications; Workforce Utilization Rate, which measures how effectively HR are utilized; the Performance Efficiency Score, which measures productivity or output quality; the Workload Intensity, which measures the workload of an employee and whether they feel they are working too much or too little; and the Voyage Duration Index which considers how the duration of assignments or travel is affecting an employee's capacity. To validate these indicators, they should be subjected to the feature importance analysis to assess whether these engineered workforce indicators are actually making a contribution to the improvements in the prediction accuracy and whether they are adding value in managerial decision making and strategic workforce planning.

Figure 4: Analysis on Feature Importance.



Source: Authors.

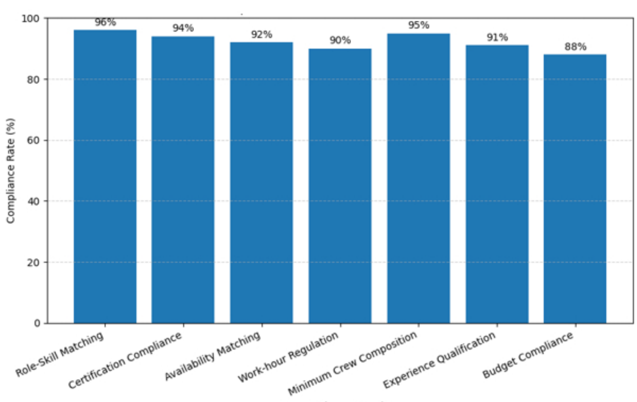
The Retention Score, Fatigue Risk Index and Skill Gap Score are the top three features for the prediction of workforce outcomes within the proposed maritime HR analytics framework as indicated in the Feature Importance Evaluation shown in Figure 4. This indicates that the top two triggers impacting on talent forecasting and workforce planning are employee retention action and employee fatigue / competency gaps. Certification Validity (0.12) and Workload Intensity (0.10) also play key roles in the prediction accuracy, and Performance Efficiency, Voyage Duration and Training Need Score play moderate roles. The overall findings indicate that the Random Forest model can accurately identify the most important indicators on a maritime workforce, which are useful for accurate prediction and effective strategic maritime human resource decision-making.

iii. Constraint Validation Performance.

For workforce optimization, constraint checking performance is essential as solutions could be very efficient, but they still need to be feasible, compliant and workable in real-life situations. In order to ensure this, several key indicators are assessed, such as the role–skill matching percentage, which determines if assigned personnel have the necessary skills for the job they are assigned to do; the certification compliance percentage, which verifies that the employees have the valid and required certifications; the personnel availability matching rate, which checks if the personnel are available at the right time and in the right location when required; the working hours regulation adherence, which checks if the working hours are within the legal and organizational limits; the personnel at work minimum crew composition satisfaction, which confirms that the minimum size and distribution of staffing members required for the job is met; the experience qualification matching rate, to check if assigned personnel have the necessary level of experience for the job to be able to do; and the budget compliance rate, which checks if the workforce deployment is within the budget. These indicators confirm optimized workforce allocation is efficient and in addition safe, compliant and operationally sustainable.

The numbers in the Constraint Validation Performance results (Figure 5) indicate that the proposed maritime workforce optimization framework has a high compliance level for most operational constraints. The highest performances were found in the following areas: Role-Skill Matching (96%), Minimum Crew Composition (95%), demonstrating that qualified personnel and staffing level requirements are shown. The workforce allocation for regulatory/operational requirements (as measured by Strong Compliance) is reliable (94%), with Experience Qualification Matching (91%) and Availability Matching (92%) also being reliable. The figure 6 for Budget Compliance (88%) and Work-hour Regulation (90%) are relatively low but are good indications of cost and workload management. The results in general support the proposed framework to address the main constraints of the maritime sector, to optimize, comply and operate the crew.

Figure 5: Analysis on Constraint Validation Performance.



Source: Authors.

Conclusions.

This research aimed to create a data-driven and intelligent approach to transform traditional maritime HRM and present a Smart Maritime HR Analytics Framework for Talent Forecasting and Operational Efficiency. The framework integrates structured survey-based workforce data, cutting-edge preprocessing and feature engineering techniques, Random Forest predictive analytics, Genetic Algorithm workforce optimization, multi-constraint validation, and an interactive decision support dashboard, offering a comprehensive solution to address critical maritime workforce challenges such as talent scarcity, employee turnover, skill shortages, fatigue, compliance monitoring, and operational inefficiencies. The predictive evaluation results indicated good predictive power while feature importance analysis results identified that the factors of retention, fatigue and competency alignment have been found to be important for the determination of workforce. Furthermore, the results from the optimization and constraint validation verifications showed that the framework developed was able to provide feasible, compliant, and efficient crew deployment strategies.

To conclude, the proposed model offers a proactive strategy to make intelligent decisions in maritime workforce management through data-driven solutions, which cover aspects of recruitment planning, targeted training and development, optimized crew scheduling, enhanced retention strategies, and operational decisions. Predictive modelling and optimisation, as well as increasing the resilience of the maritime workforce and regulatory readiness, also supports sustainable operational efficiency. As maritime organisations continue to progress with their digital transformation, this framework can be used as a template for future smart HR systems that will be continuously learning, real-time monitoring of workforce and evidence-based human capital planning. The proposed work therefore has significant potential to help build the overall efficiency, resilience and sustainability of modern maritime HR analytics in providing workforce management practices.

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