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DEVELOPMENT OF A NAVIGATOR QUALIFICATION MODEL FOR AUTOMATED SHIP HANDLING CONTROL TASKS

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The study aims to develop a comprehensive qualification model for navigators in automated ship control, evaluating technical, cognitive, and behavioral competence to enhance real-time decision-making in variable navigational environments.
The main challenge is integrating advanced technologies like artificial intelligence and fuzzy logic to accurately monitor risks arising from human factors.
The methodology involves creating a model that assesses navigator competencies by integrating various aspects. Data from ECDIS and other sensors are processed into a feature vector. The Mamdani algorithm aggregates fuzzy rules defining qualification parameters, while neural networks model complex interrelationships. The model uses fuzzy membership functions to assess risks considering speed, under-keel depth, weather conditions, and collision probability.
Results show the model detects potential risks timely and automates decision-making, reducing navigator workload in challenging conditions. It effectively predicts ship trajectory, identifies risky zones, and provides safety recommendations.
Practically, it enhances maritime safety through personalized navigator assessment. Integration with existing systems like ECDIS offers flexibility without major infrastructural changes. The system individualizes recommendations, reducing accident risk and improving training efficiency. Future research includes expanding the training database, refining algorithms, and studying the impact of the navigator's psychophysiological state on ship management effectiveness.
Key words: *steering control; optimization of control processes; automatic control module; emergency situations; traffic flows; information support; Safety Depth; ECDIS; maneuvering in confined waters; recognition system.*

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Introduction. With global maritime traffic increasing by over 60% and navigational situations becoming more complex, modern shipping faces challenges that demand high navigator preparedness and rapid adaptation. Key issues include managing ships during complex maneuvers – such as navigating narrow straits, limited visibility, high traffic density, and changing weather conditions. Despite advanced decision support and navigational information systems, much responsibility relies on the navigator's qualifications, decision-making abilities, and quick analysis of surrounding factors.

Existing systems like ECDIS, AIS, GPS, and autopilots provide extensive data but often neglect the navigator's cognitive and behavioral aspects, which are crucial in complex situations. Overreliance on automated decision support can lead to excessive dependence, insufficient situational awareness, and potential loss of control during critical moments, especially in difficult sailing conditions. This problem is particularly acute concerning possible collisions, limited under-keel depth, and risks from heavy traffic in high-danger zones.

Traditional decision support systems may not fully account for rapid external changes – like sudden weather shifts or other vessels' course changes – and often emphasize theoretical knowledge over behavioral model development. The absence of a comprehensive navigator model that includes both technical and cognitive aspects poses significant risks to maritime safety and complicates automated control under increased workloads.

Therefore, developing a navigator qualification model for automated ship control tasks is urgently needed to provide objective assessments and enhance the efficiency and reliability of automated ship control systems in complex navigational conditions.

Problem Statement. An analysis of scientific sources shows various approaches to automation and risk assessment in maritime navigation, with a particular emphasis on the use of fuzzy logic, neural networks, and artificial intelligence.

In article [1], an adaptive neuro-fuzzy inference system (ANFIS) is proposed for a ship's autopilot in unstable environments. Advantages include adaptability to external conditions and the ability to model complex maneuvers thanks to six degrees of freedom. However, the complexity of the system and dependence on precise parameter tuning may limit its application for assessing the navigator's qualification. Work [2] presents a method of multisensor data fusion for detecting moving objects using fuzzy logic. This increases the reliability of target detection, which is useful for the navigator's situational awareness. However, the focus on automatic determination of object positions without considering the human factor limits its application for qualification assessment. In article [3], a risk assessment model is proposed for marine aquaculture platforms, using AIS data to analyze shipping traffic. The model considers numerous environmental factors but is more oriented towards objective data and less towards the behavioral aspects of the navigator. Study [4] examines the implementation of fuzzy logic controllers in automatic navigation using IoT and genetic algorithms. Although aimed at automotive navigation, the principles can be adapted for the marine environment. However, the lack of emphasis on behavioral indicators and the specificity of the marine environment require additional adaptation. Article [5] presents a method of risk assessment using 3,4-quasi-level fuzzy sets and a multicriteria decision-making system. The approach demonstrates flexibility and improved accuracy in risk determination, which is valuable for assessing the navigator's qualification in complex conditions. However, the complexity of customization for the maritime environment and limitations in assessing behavioral characteristics can be obstacles. Article [6] proposes a model that uses AIS data and global optimization algorithms to mitigate conflicts between ships. Advantages include integration of situational awareness and assessment of high-risk zones. However, the lack of attention to behavioral characteristics of the navigator and real-time limitations may reduce the practicality of the method for qualification assessment. In study [7], the perception of navigators towards the collision avoidance decision support system (AIM) is analyzed. The system enhances situational awareness and promotes compliance with COLREGs rules. However, dependence on automatic recommendations and a limited role of traditional skills may limit its effectiveness in the context of qualification assessment.

Article [8] explores modern visual navigation systems for "smart" ships, focusing on the integration of data from various sensors and intelligent algorithms. This promotes increased navigation safety and can be integrated into qualification models for developing environmental analysis skills. However, dependence on technologies and high resource requirements can become obstacles. In work [9], a hybrid model is proposed for assessing navigation risks of autonomous ships by combining STPA and hidden Markov models. This allows identifying risk factors in dynamic conditions. However, the complexity of integrating behavioral aspects and dependence on data accuracy limit its application for qualification assessment. Article [10] explores the impact of augmented reality (AR) on navigator performance. The use of AR enhances situational awareness and can be useful for assessing the ability to effectively manage navigation. However, potential cognitive overload and lack of standardization require further research. In article [11], possibilities for standardizing ECDIS through the implementation of S-Mode are analyzed, aimed at reducing human errors by unifying the interface. This can help in assessing adaptability and competence of the navigator in using standardized systems. However, challenges related to the need for specific training and problems adapting to older models are present. Work [12] presents the RA4MAIS method for identifying risks of integrated AI-based systems for remotely controlled ships. The method considers internal failures, human errors, and environmental conditions. However, limited practical testing and the complexity of integration with traditional risk analysis methods may be obstacles.

In [13], a methodology for merging AIS and radar data is investigated to enhance situational awareness on inland waterways. This improves the accuracy of navigational data and helps in detecting potential hazards. However, the complexity of algorithms and sensitivity to data quality may complicate practical application. Article [14] examines the interaction of watch officers with the ECDIS system and the impact of interface variability from different manufacturers on navigation safety. Standardization of the interface can reduce the number of human errors, but the lack of a unified standard and complexity in real-world use limit the effectiveness of the approach. Study [15] proposes a model for enhancing navigation safety by analyzing errors in the use of AIS. Emphasis on additional training and standardization of educational programs contributes to improving technical awareness of navigators. However, the narrow focus on AIS errors and lack of attention to cybersecurity reduce the comprehensiveness of the approach. In article [16], a method for predicting navigational behavior of ships based on AIS data using the Attention-LSTM neural network is proposed. This achieves high prediction accuracy, which can improve maritime traffic monitoring. However, high resource requirements and dependence on data quality are limitations.

Article [17] describes a method based on computer vision for assessing the risk of collision between ships, using the YOLOv7 model and the StrongSORT algorithm. Advantages include high accuracy in object detection and tracking, allowing assessment of the navigator's skills in hazard detection. Disadvantages include sensitivity to weather conditions and dependence on camera stability. Articles [18–21] explore the adaptive capabilities of Learning Management Systems (LMS) and their application for improving navigator training. The use of early success prediction models and a systematic approach to LMS implementation can increase learning efficiency. However, the complexity of managing large data volumes and lack of standardization may limit effectiveness. In work [22], a dynamic ship domain model is proposed that takes into account traffic, speed, and the navigator's state. This allows assessing the navigator's adaptability to external conditions. However, computational complexity and dependence on data quality limit practical application.

Articles [23–25] are devoted to improving OCR technologies for processing textual data, which can be useful for automating the processing of navigational documents. However, dependence on image quality and high resource requirements may limit application in the maritime environment.

In article [26], the use of mixed reality for improving maritime navigation is investigated, especially under conditions of remote piloting. Advantages include increased situational awareness, but high hardware requirements and possible visual overload are disadvantages. Article [27] analyzes the implementation of competency-based education in the training of maritime specialists. This promotes increased qualification and navigation safety but requires overcoming financial and organizational barriers.

Overall, the analyzed sources demonstrate a wide range of modern technologies and methods that can be integrated to develop effective models for assessing the navigator's qualification, considering technical and behavioral aspects.

Research Purpose and Objectives. The purpose of the study is the development of a qualification model of the navigator for automated ship control, which will provide a comprehensive assessment of his professional competencies, including technical, cognitive, and behavioral aspects. The model should enhance the efficiency of decision-making in real-time, taking into account changing environmental conditions and the specific skills of the navigator for safe navigation.

Research tasks. The research aims to develop a comprehensive qualification model for navigators by:

Reviewing modern qualification assessment approaches to identify methods using fuzzy logic, neural networks, and artificial intelligence that integrate technical and behavioral aspects.

Formulating model components for systematic assessment, considering input data, hazard level evaluation, qualification parameters, and the navigator's intuitive and cognitive features.

Developing a hazard level assessment module utilizing fuzzy logic for multicriteria navigational risk evaluation, adaptable to external factors and changing conditions.

Creating algorithms to identify navigator qualification parameters based on training, test results, and real navigational scenarios to determine competencies critical for safe navigation.

Developing a cognitive module to analyze navigators' intuitive actions in critical situations, accounting for human factors and assessing risks associated with intuitive decision-making.

Creating modules for ship trajectory prediction and decision-making to analyze trajectories, identify potentially dangerous zones, and provide recommendations to enhance navigation safety.

Ensuring integration with existing navigation systems, particularly ECDIS and AIS, for accurate real-time data processing and timely assessment of the navigator's qualification level and safety.

Primary Research Material. The development of a Navigator Qualification Model (NQM) is based on four key principles:

Comprehensive Assessment: Consider both technical and human factors in evaluating navigational situations.

Adaptability: Adjust to changing navigation conditions and individual navigator characteristics.

Safety Enhancement: Improve safety through risk prediction and providing recommendations.

Real-Time Support: Utilize modern technologies to aid decision-making in real time.

The NQM is structured into six main modules:

1. Input Data and Navigation Parameters

1.1 Data Collection: Gather navigational data (speed, course, position), information from ECDIS and AIS systems, and training results; synchronize and aggregate this data.

1.2 Data Processing: Normalize and filter data to remove noise and outliers.

1.3 Feature Extraction: Extract relevant features to form the system's state vector.

2. Hazard Level Assessment Module

2.1 Fuzzy Logic Risk Assessment: Use membership functions and expert-based fuzzy rules to evaluate risks, resulting in a numerical risk value.

2.2 Mathematical Risk Model: Calculate risk levels using normalized parameters and weight coefficients to model the impact of individual factors.

3. Navigator Qualification Parameters Module

3.1 Qualification Identification: Collect data on test results, training activities, and simulator performance; normalize and filter to create feature vectors.

3.2 Competency Modeling: Define competencies and levels using fuzzy logic; apply neural networks to model complex relationships.

3.3 Model Training: Train neural networks with historical data; optimize weights and validate the model.

3.4 Gap Analysis: Identify competencies below threshold levels; develop improvement plans and update the model with new data.

4. Cognitive Module of Intuitive Actions

4.1 Criteria Generalization: Consolidate intuitive actions into main categories (e.g., perception, decision-making) for simplified analysis.

4.2 Impact Modeling: Define criteria for each category; assess their impact on safety and model them as variables affecting risk levels.

5. Navigational Data and Geolocation Processing Module

5.1 Automated Processing: Capture ECDIS screenshots; preprocess images; use OCR for text recognition.

5.2 Data Analysis: Structure textual data; calculate distances between coordinates; detect deviations from planned routes.

5.3 Visualization: Create interactive maps displaying routes and risk zones to enhance situational awareness.

5.4 System Integration: Transfer processed data to other modules for comprehensive analysis and recommendation generation.

6. Forecasting and Decision-Making Module

6.1 Trajectory Prediction: Use machine learning algorithms to predict future ship positions; adapt models to specific ship conditions.

6.2 Risk Detection: Analyze predicted trajectories for potential hazards; consider uncertainties and human factors.

6.3 Decision Support Integration: Incorporate forecasting results into decision support systems; generate recommendations based on data analysis.

6.4 Recommendation Delivery: Provide timely advice to optimize decisions; display recommendations on interfaces and interactive maps.

An important condition in the development of the NQM is considering the interaction between its components. The development of the NQM involves creating the following connections (Figure 1):

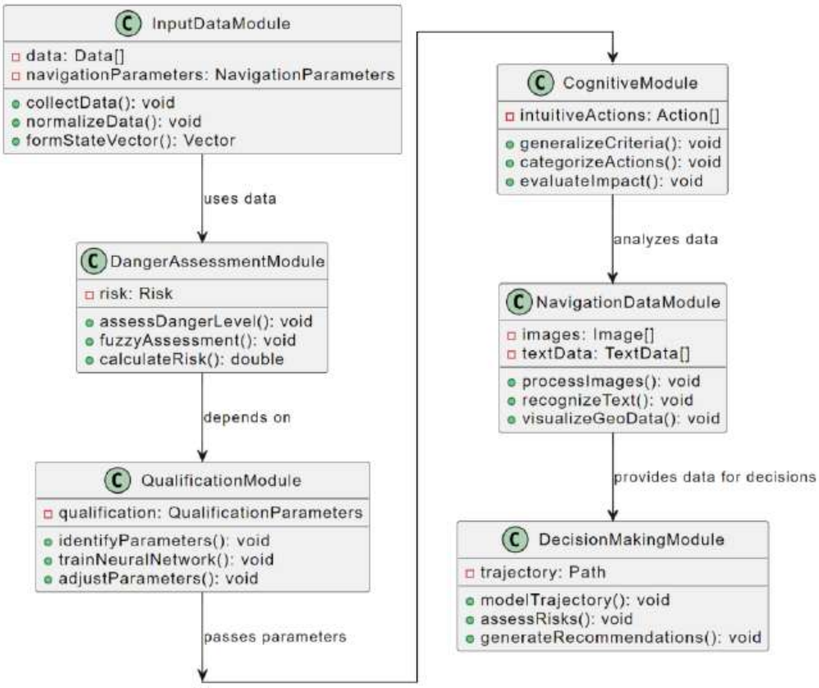

Figure 1 – Scheme of interaction between components of the navigator's qualification model

Input data provide information for all modules, supporting the relevance and accuracy of the analysis.

The hazard level assessment module uses data from navigational parameters and the navigator's qualification to calculate risks.

The module for identifying qualification parameters influences risk assessment, considering the navigator's level of competencies.

The cognitive module of intuitive actions takes into account the human factor and can adjust forecasting and recommendations.

The navigational data processing module provides current and accurate data for the forecasting and decision-making modules.

The forecasting and decision-making module integrates information from all modules for comprehensive analysis and navigator support.

Let us consider each module of the NQM model in detail.

2. Description of NQM Input Data and Navigation Parameters (Figure 2).

2.1. Data Collection.

Navigational parameters: (Ship speed $S(t)$; Ship course $\theta(t)$; Ship position $(x(t), y(t))$; Proximity to other ships $P(t)$; Technical condition of the ship $T_s(t)$; Weather conditions $W(t)$; Time of day $C(t)$; Under-keel clearance $H(t)$; Current $V_{\text{current}}(t)$; Wind $V_{\text{wind}}(t)$; Visibility $Vis(t)$; Traffic intensity $D(t)$; Hazardous zones $Z_{\text{danger}}(x,y)$; Ship draft D_{draft}; Ship maneuvering characteristics $M(t)$.

Data from ECDIS and AIS Systems (Detailed electronic navigation charts; Data about other ships: position, course, speed, type) [28].

Data from LMS Moodle (Test results R_{test}; Navigator's activity A_{LMS}; Learning history H_{learning}).

Data from Simulators and VR Systems (Navigator's reactions in various scenarios $R_{\text{sim}}(t)$; Reaction time $T_{\text{reaction}}(t)$; Maneuvering accuracy $Acc_{\text{maneuver}}(t)$).

2.2. Data Preprocessing and Integration into the Model.

A description of how collected data from various sources are preprocessed and integrated into the navigator's qualification model for real navigational situations.

2.2.1. Data Synchronization and Aggregation.

Time Synchronization: Since data arrive from different sources with various timestamps and update frequencies, it is necessary to synchronize them to a common time step Δt. A common time scale is established $t_1,t_2,...,t_T$, where T is the number of time intervals.

Interpolation and Discretization: Data with a higher frequency are aggregated to Δt by averaging. Data with a lower frequency are interpolated to obtain values at each t_k.

Data Aggregation: All parameters for each time moment t_k are combined into a single state vector $x(t_k)$.

2.2.2. Normalization and Scaling of Parameters.

To ensure the correctness and stability of the model operation, all parameters are normalized to the range [0,1] or standardized (Z-score normalization).

Min-Max Normalization: $x_{norm} = \dfrac{x - x_{\min}}{x_{\max} - x_{\min}}$, Z-Score Normalization: $x_{\text{std}} = \dfrac{x - \mu_x}{\sigma_x}$,

where μ_x is the mean value of parameter xxx, and x, σ_x is the standard deviation.

Application of Normalization: Navigational parameters $S(t)$, $\theta(t)$, $P(t)$, $T_{\text{s}}(t)$, $W(t)$, $H(t)$, $V_{\text{current}}(t)$, $V_{\text{wind}}(t)$, $Vis(t)$, $D(t)$ are normalized using the appropriate methods.

2.2.3. Data Processing and Filtering.

Noise Filtering: Low-pass filters or the Kalman filter are applied to smooth data and remove noise.

Outlier Detection and Processing: Statistical methods are used to detect abnormal values (e.g., quartile method). Outliers can be replaced with the median value or removed from the dataset.

2.2.4. Extraction of Relevant Features.

Based on the normalized and cleaned data, features are formed to be used in the model.

Navigational Features: Ship speed $S_{\text{norm}}(t)$; Ship course: $\theta_{\text{norm}}(t)$; Deviation from planned course: $\Delta\theta_{norm}(t) = \theta_{norm}(t) - \theta_{planned,norm}(t)$; Proximity to other ships: $P_{\text{norm}}(t)$; Under-keel clearance: $H_{\text{norm}}(t)$; Visibility: $Vis_{\text{norm}}(t)$.

Environmental Features – Weather conditions: parameters $W_{\text{norm}}(t)$ are split into separate features (wind, waves, etc.). Current and wind $V_{\text{current, norm}}(t)$, $V_{\text{wind, norm}}(t)$.

Technical Features: Technical condition of the ship: $T_{\text{s,norm}}(t)$; Maneuvering characteristics: parameters $M_{\text{norm}}(t)$ may include turning radius, stopping distance, etc.

Qualification Features: est results: aggregated into a single indicator or vector $R_{\text{test, norm}}$; Activity in LMS Moodle: $A_{\text{LMS, norm}}$; Data from simulators and VR systems: $R_{\text{sim, norm}}(t)$, $T_{\text{reaction, norm}}(t)$ $Acc_{\text{maneuver, norm}}(t)$.

2.2.5. Formation of the System State Vector.

All extracted features are combined into a single state vector for each moment in time t: $x(t)$=[$S_{\text{norm}}(t)$, $\theta_{\text{norm}}(t)$, $P_{\text{norm}}(t)$, $H_{\text{norm}}(t)$, $Vis_{\text{norm}}(t)$, $V_{\text{current, norm}}(t)$, $V_{\text{wind, norm}}(t)$, $T_{\text{s,norm}}(t)$, $R_{\text{sim, norm}}(t)$, $T_{\text{reaction, norm}}(t)$, $Acc_{\text{maneuver, norm}}(t)$, $R_{\text{test, norm}}$, $A_{\text{LMS, norm}}$,…].

2.2.6. Mathematical Formalization of the Model

The navigator's qualification model in a real situation can be represented as a function: $k(t)=f(\mathbf{x}(t), \Theta^*)$, where: $k(t)\in[0,1]$ - is the navigator's qualification assessment at time t.

$\mathbf{x}(t)$ - is the system state vector at time t.

Θ^* are the model parameters requiring adjustment (weight coefficients, activation function parameters, etc.).

Possible Forms of Function f:

Linear Regression: $k(t) = \mathbf{w}^\top\mathbf{x}(t)+b$, where $\mathbf{w}$ - is the weight coefficient vector, and b is the bias.

Nonlinear Model (Neural Network): $k(t) = \sigma(\mathbf{w}_2\top\phi(\mathbf{W}_1x(t)+\mathbf{b}_1)+\mathbf{b}_2)$,

where: $\mathbf{W}_1$, $\mathbf{w}_2$ - are the weight matrix and vector, respectively.

$\mathbf{b}_1$, $\mathbf{b}_2$ - are bias vectors.

$\phi(\cdot)$ - is the activation function of the hidden layer (e.g., ReLU).

$\sigma(\cdot)$ - is the sigmoid function to limit the output in the range [0,1].

Fuzzy Logic Model: Fuzzy rules are used to model the relationships between features and qualification. Defuzzification of results is performed to obtain a numerical value $k(t)$.

2.2.7. Determination of Model Parameters.

Model Training: Historical data with known qualification assessments $k_{\text{true}}(t)$ are used to adjust parameters Θ^*.

Minimization of Loss Function: $L=\frac{1}{T}\sum_{t=1}^{T}\left(k(t)-k_{true}(t)\right)^2$.

Parameter Optimization: Performed using gradient descent methods or its variations.

Regularization: To prevent overfitting, regularization methods are used (L_1, L_2 regularization, Dropout in the case of neural networks).

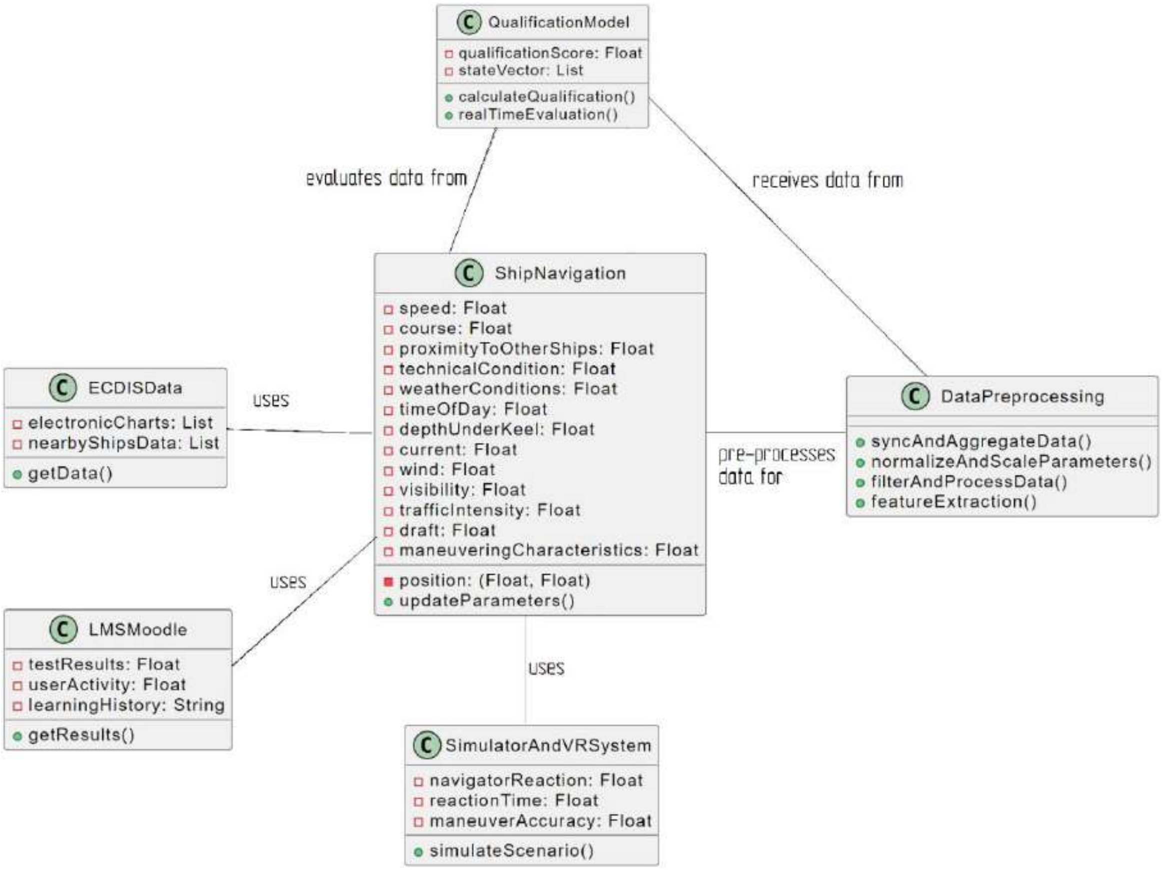

Figure 2 – Data Collection Module for the Navigator's Qualification Model

2.2.8. Model Validation and Testing.

Data Partitioning: Data are divided into training, validation, and test sets. Evaluation of Model Quality Metrics. Mean Squared Error (MSE). Coefficient of Determination (R^2).

2.2.9. Real-Time Model Usage.

Real-Time Qualification Assessment: is calculated in real-time based on current parameter values $k(t)$, $x(t)$.

Integration with Navigation Automation System: If $k(t)$ falls below a certain threshold $k_{\text{thresholdk}}$, the system can activate additional control or support mechanisms.

Consideration of Psychophysiological State: The parameter $k(t)$ can be adjusted taking into account the navigator's psychophysiological $S(t)$, as described earlier.

3. Hazard Level Assessment Module (Figure 3).

3.1. Fuzzy Logic and Multicriteria Risk Assessment.

3.1.1. Membership Functions for Each Parameter.

For the parameter x_i, Gaussian, triangular membership functions, and others are used:

Gaussian Function: $\mu_i\left(x_i\right)=e^{-\frac{\left(x_i-c_i\right)^2}{2\sigma_i^2}}$,

where c_i – is the mean value, σ_i – is the standard deviation.

Triangular membership functions and others can also be applied.

3.1.2. Fuzzy Rules (Knowledge Base Rules).

"If–then" type rules that take into account maritime transportation experience:

Rule 1: If $S(t)$ is high, and $P(t)$ is low, and $Vis(t)$ is poor, then the risk is critical.

Rule 2: If $H(t) - D_{\text{draft}}$ is small (under-keel clearance is low) and $V_{\text{current}}(t)$ is strong current, then the risk is high.

3.1.3. Aggregation and Defuzzification.

Aggregation: Performed using T-norm (minimum) or S-norm (maximum)

Defuzzification using the Center of Gravity Method

$$R=\frac{\int r\cdot\mu_R\left(r\right)dr}{\int\mu_R\left(r\right)dr}$$

3.2. Mathematical Risk Model Using Analytical Functions.

We describe the risk as a function:

$$R\left(t\right)=\frac{\sum_{i=1}^{n}w_i\cdot f_i\left(x_i\left(t\right)\right)}{\sum_{i=1}^{n}w_i}.$$

where: w_i – are weighting coefficients determined by experts.

$f_i(x_i(t))$ – are normalized risk functions for each parameter.

Example of a Risk Function for Under-Keel Clearance:

$$f_H\left(H\left(t\right)\right)=\begin{cases}1, & H\left(t\right)-D_{draft}\le H_{\min}\\ \dfrac{H\left(t\right)-D_{draft}-H_{\min}}{H_{safe}-H_{\min}}, & H_{\min}<H\left(t\right)-D_{draft}<H_{safe}\\ 0, & H\left(t\right)-D_{draft}\ge H_{safe}\end{cases}$$

4. Module for Identifying the Navigator's Qualification Parameters

4.1. Algorithm for Identifying Qualification Parameters

4.1.1. Problem Statement

The goal of this module is to develop a mathematical model and algorithm for the automated identification of the navigator's qualification parameters based on the training program for specialization 271.01 "Navigation and Control of Marine Vessels." The model should consider all aspects of professional competence provided by the program and utilize various data sources to assess the navigator's level of preparation.

4.1.2. Data Collection and Preliminary Processing

Data Sources:

a) Learning Management System (LMS Moodle): Test Results: $R_{test} = \{r_1, r_2, ..., r_n\}$, where: $r_j \in [0,100]$ – is the percentage result of the j-th test. Navigator's Activity: $A_{LMS}=\{a_1, a_2, ..., a_m\}$, where: a_i – are activity indicators in LMS (number of logins, time spent on the platform, completed tasks, etc.). Learning History: $H_{learning}$ – records of completed courses, obtained certificates, etc.

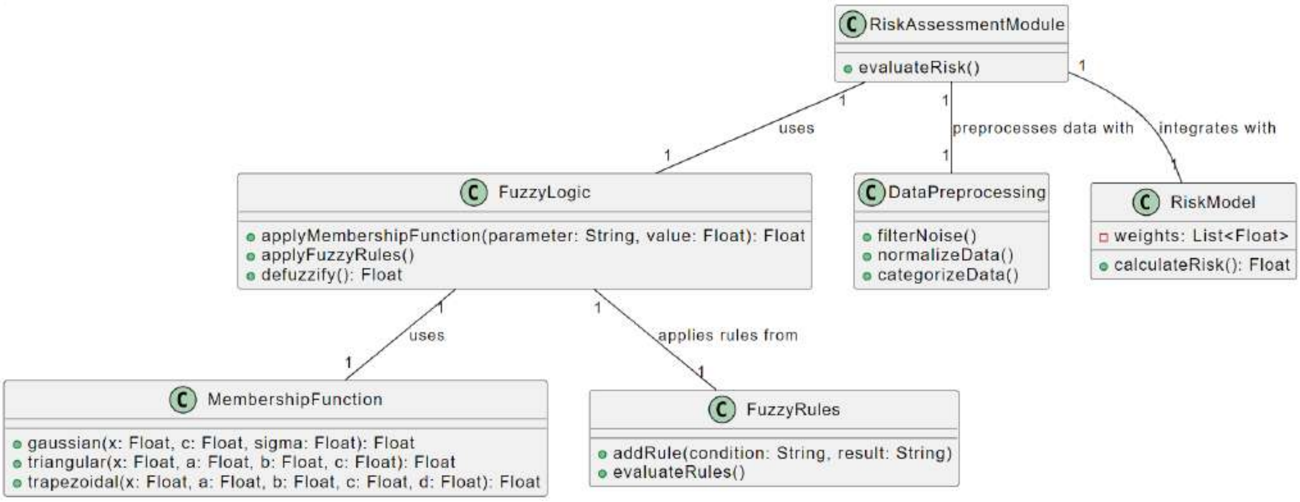

Figure 3 – Scheme of the Hazard Level Assessment Module

b) Тренажери та VR-системи: Navigator's Reactions in Simulated Situations: $R_{sim}=\{s_1, s_2, ..., s_k\}$, where: s_k – is a set of indicators for the k-th simulated situation.

Reaction Time: $T_{reaction} = \{t_1, t_2, ..., t_k\}$, where: t_k is the reaction time to the k-th situation.

Maneuvering: $Acc_{maneuver} = \{acc_1, acc_2, ..., acc_k\}$, where: $acc_k \in [0,1]$ – is the accuracy of executing the k-th maneuver.

c) Data from Real Navigational Operations: Actions During Watch: $D_{actions} = \{d_1, d_2, ..., d_l\}$, where: d_l is a set of actions performed during the l-th watch.

Deviation from Planned Route: $\Delta_{route} = \{\delta_1, \delta_2, ..., \delta_l\}$, where: δ_l is the deviation from the route during the l-th watch.

Decisions Made in Critical Situations: $D_{decisions}=\{dec_1, dec_2, ..., dec_p\}$, where: dec_p is the quality assessment of the decision in the p-th critical situation.

Preliminary Data Processing. Normalization: Bringing data to a common scale [0,1] to ensure correctness in subsequent calculations.

Normalized indicator: $x_{norm} = \dfrac{x - x_{\min}}{x_{\max} - x_{\min}}$, where: x is the original value; $x_{\min}$, $x_{\max}$ – are the minimum and maximum values of the indicator.

Filtering: Removal of noise and anomalous values using the Kalman filter or other methods.

Feature Extraction: Forming a feature vector X for each navigator: $X = [x_1, x_2, ..., x_N]$ – is the total number of features obtained from all data sources.

4.1.3. Mathematical Model of Qualification Parameters

Definition of Qualification Parameters. Let there be a set of qualification parameters $K = \{k_1, k_2, ..., k_M\}$, where: $k_i \in [0,1]$ is the level of proficiency in the i-th competence. M is the number of competencies defined based on the training program.

Sets of Qualification Parameters: k_1: Knowledge of International Regulations for Preventing Collisions at Sea (COLREG); k_2: Skills in maneuvering under complex conditions; k_3: Ability to make decisions in critical situations; k_4: Technical proficiency in using navigation equipment; k_5: Level of fatigue and psychophysiological state.

Formation of Membership Functions.

For each qualification parameter k_i membership functions $\mu_{ki}(x)$, are defined, reflecting the navigator's degree of proficiency in the corresponding competence.

Building a Fuzzy Rule Base. Нечіткі правила мають виг Fuzzy rules have the form: If x_1 belongs to A_1 and x_2 belongs to A_2 then k_i belongs to K_i, where: x_1, x_2 are features from vector X; A_1, A_2 are linguistic terms (e.g., "high," "medium," "low"); K_i is the linguistic assessment of competence k_i.

Mathematical Model of Identification. Aggregation of Rules: The Mamdani method is used for rule aggregation. The activation degree of each rule is calculated as the minimum of the membership degrees of the input features.

4.1.4. Data Processing and Qualification Parameter Assessment

Formation of Feature Vector X. The feature vector X consists of normalized values of indicators affecting the qualification parameters: $X = [x_1, x_2, ..., x_N]$, де: $x_n \in [0,1]$ is a normalized indicator.

Use of Neural Networks. To model complex nonlinear relationships between features and qualification parameters, a multilayer perceptron (MLP) neural network is used.

Network Architecture: Input Layer: N neurons (number of features).

Hidden Layers: One or more layers with nonlinear activation functions (ReLU, sigmoid, tanh).

Output Layer: M neurons (number of qualification parameters).

Output of a Hidden Neuron: $h_j = f_{hidden}\left(\sum_{n=1}^{N} w_{nj}x_n + b_j\right)$,

where: h_j is the output of the j-th hidden neuron.

w_{nj} is the weight coefficient between the n-th input neuron and the j-th hidden neuron

b_j is the bias of the j-th hidden neuron

$f_{\text{hidden}}(\cdot)$ is the activation function of the hidden layer.

Output of the Output Neuron (Qualification Parameter):

$$k_i = f_{output}\left(\sum_{j=1}^{H} w_{ji}h_j + b_i\right),$$

where: H is the number of neurons in the hidden layer.

w_{ji} is the weight coefficient between the j-th hidden neuron and the i-th output neuron.

b_i is the bias of the i-th output neuron.

$f_{\text{output}}(\cdot)$ is the activation function of the output layer (e.g., sigmoid).

4.1.5. Neural Network Training

Loss Function. The Mean Squared Error (MSE) function is used:

$$L = \frac{1}{M}\sum_{i=1}^{M}\left(k_i^{pred} - k_i^{true}\right)^2,$$

where: k_i^{pred} is the predicted value of qualification parameter k_i,

k_i^{true} is the actual (reference) value of qualification parameter k_i.

Optimization of Weight Coefficients. The backpropagation algorithm is used. Optimizers include SGD (Stochastic Gradient Descent), Adam, RMSProp.

Hyperparameters: Learning rate η\etaη, batch size, number of epochs.

Validation and Testing. Data are divided into training, validation, and test sets. Quality metrics are evaluated: MSE, MAE (Mean Absolute Error), coefficient of determination R^2.

4.1.6. Identification and Correction of Qualification Gaps

Detection of Critical Parameters. A threshold value $k_i^{threshold}$ is set for each qualification parameter. If $k_i < k_i^{threshold}$, then competence k_i requires improvement.

Forming a Knowledge Recovery Plan. Determining educational materials and training to increase the level of k_i. Monitoring progress after training.

4.1.7. Impact of Qualification Parameters on Risk Level

Calculation of Integral Qualification Indicator: $Q = \frac{\sum_{i=1}^{M} v_i k_i}{\sum_{i=1}^{M} v_i}$,

where: v_i is the weighting coefficient of the importance of competence k_i.

$Q \in [0,1]$ is the integral qualification indicator of the navigator.

Risk Level Adjustment. The risk level R is adjusted considering the navigator's qualification: $R_{\text{adjusted}} = R \cdot (1+\alpha(1-Q))$,

where: R is the base risk level determined based on navigational parameters.

$\alpha \geq 0$ is the coefficient of the qualification's impact on risk.

4.1.8. Considering Psychophysiological State

Psychophysiological State Model.

Psychophysiological state coefficient $S \in [0,1]$: $S = e^{-\beta F}$,

where: $F \geq 0$ is the level of fatigue or stress,

$\beta \geq 0$ is the coefficient of fatigue's impact on the state.

Adjustment of Qualification Paramete. Effective qualification parameter: $k_i^{eff} = k_i \cdot S$

Impact on Risk Level. Final risk level: $R_{\text{final}} = R_{\text{adjusted}} \cdot (1+\gamma(1-S))$,

where: $\gamma \geq 0$ is the coefficient of the psychophysiological state's impact on risk.

4.1.9. Dynamics of Qualification Parameter Changes

Learning and Forgetting Model: $\frac{dk_i}{dt} = \mu_i U_i(t) - \lambda_i k_i(t)$,

where: $\frac{dk_i}{dt}$ is the rate of change of qualification parameter k_i, $\mu_i \geq 0$ is the learning coefficient.

$U_i(t) \geq 0$ is the intensity of learning at time t, $\lambda_i \geq 0$ is the forgetting coefficient.

With constant $U_i(t) = U_i$: $k_i(t) = \left(k_i(0) - \frac{\mu_i U_i}{\lambda_i}\right) e^{-\lambda_i t} + \frac{\mu_i U_i}{\lambda_i}$.

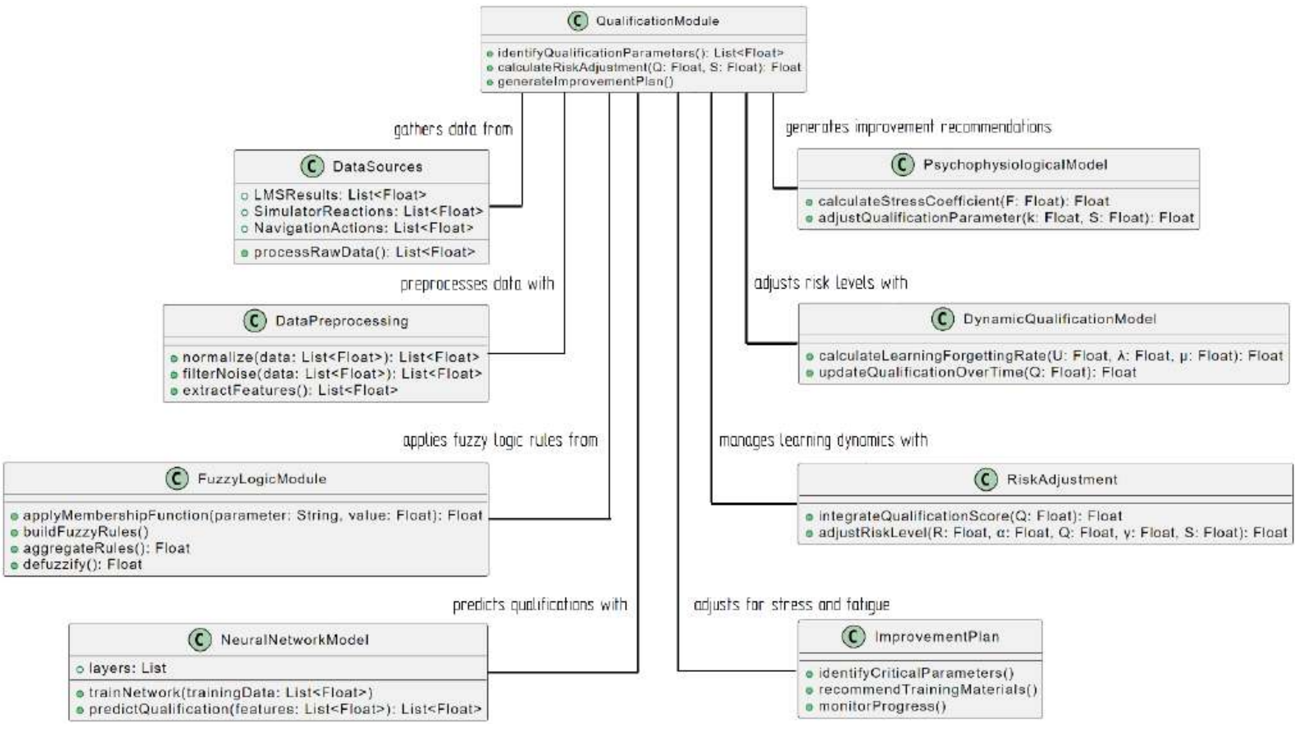

Figure 4 – Scheme of the Module for Identifying the Navigator's Qualification Parameters

Thus, the extended mathematical model for identifying navigator qualification parameters integrates elements of fuzzy logic and neural networks. It considers multiple data sources—

including test results, training, and real navigational actions—and models nonlinear relationships between indicators and competencies using neural networks. Fuzzy inference rules address uncertainty and subjectivity in assessments. The model accounts for the dynamics of qualification changes over time, considering learning and forgetting processes, and includes the impact of the navigator's psychophysiological state on effective qualification and risk levels. Additionally, it allows for adjusting the risk level based on the integral qualification indicator and the navigator's current state.

5. Module for Identifying Intuitive Actions of Operator-Navigators in Critical Situations

In critical navigational situations, operator-navigators may rely on intuitive actions that, while sometimes beneficial, can lead to errors and increased navigational risk. To effectively manage these risks, it is necessary to develop a model that identifies and analyzes navigators' intuitive actions by generalizing various criteria and combining them into more general categories [29].

5.1. Module Objective

Develop a generalized model for identifying intuitive actions of operator-navigators in critical situations.

Generalize and combine criteria of intuitive actions into general categories to simplify analysis.

Enable real-time identification of intuitive actions to manage navigational risks.

5.2. Generalization of Criteria and Combination into Categories

Define 15 initial categories of intuitive actions and combine them into five main categories. Each category includes relevant criteria, manifestations, and factors.

1: Perception and Assessment of the Situation.

Description: Intuitive perception and assessment of the navigational situation without detailed analysis. Quick awareness of changes, sometimes without proper consideration of all factors.

Combined Initial Categories: Category 1: Perception and assessment of the situation. Category 11: Time reflection. Category 14: Influence of event experience.

Criteria: Making decisions too quickly without detailed analysis. Spontaneous determination of time frames for action execution. Subconscious use of past experience in current new decisions.

Factors: $Z\alpha_{\text{int}}$ – intuitive perception of the situation; $Time_{\text{int}}$ – intuitive time reflection; $Echo_{\text{int}}$ – intuitive "echo" of events.

2: Decision-Making and Action Selection.

Description: Intuitive decision-making in critical situations. Choosing actions based on a "feeling" of correctness without objective justifications.

Combined Initial Categories: Category 2: Dynamics of intuition and action selection. Category 6: Decision-making in critical situations. Category 7: Search for rewards and effects. Category 8: Serendipity and intuition.

Criteria: Sudden feeling of the "correctness" of actions. Quick decisions without prolonged analysis. Intuitive determination of the safest actions. Sudden discovery of solutions without an obvious reason.

Factors: τ_{int} – intuitive choice; Ev_{int} – intuitive response to events; $Rewards_{\text{int}}$, $Effects_{\text{int}}$ – intuitive perception of rewards and consequences; $Idea_{\text{int}}$ – intuitive formation of ideas.

3: Cognitive Processes and Information Processing.

Description: Intuitive understanding of complex information and associative connections. Subconscious processing of navigational data and images.

Combined Initial Categories: Category 3: Cognitive processes. Category 12: Complex images and events. Category 5: Complex behavior model.

Criteria: Instant understanding of complex information. Intuitive perception of images and navigational schemes. Multitasking without conscious focus.

Factors: $Cog_{\text{int}}(P_a,P_b)$ – intuitive understanding of action sequences; $ImageSchemas_{\text{int}}$ – intuitive perception of images; $LAoT_{\text{int}}$ – intuitive actions with tools and equipment.

4: Adaptation to Changes and Resource Management.

Description: Intuitive adaptation to new conditions without detailed analysis. Intuitive management of resources and time.

Combined Initial Categories: Category 4: Adaptation to changes. Category 9: Search for resources and time synthesis. Category 13: Time cycles and rhythms.

Criteria: Quick adaptation without analysis. Efficient use of resources and time without planning. Intuitive synchronization of work with daily cycles.

Factors: $\Xi_{int}\backslash X_i$ – intuitive adaptation; $\textit{Resource-Search}_{int}$, $\textit{Time-Synthesis}_{int}$ – intuitive management of resources and time; $\textit{Rhythms}_{int}$ – intuitive synchronization of rhythms.

5: Influence of External Factors and Features of the Navigation Area.

Description: Intuitive perception of global and local conditions affecting navigation. Subconscious consideration of navigation area features.

Combined Initial Categories: Category 10: World events. Category 15: Features of the navigation area.

Criteria: Intuitive adaptation to global navigational practices. Deep, unconscious perception of the locality.

Factors: $\textit{WorldEv}_{int}$ – intuitive perception of world events; $\textit{Ag}_{int}$ – intuitive sense of place.

Generalizing and combining criteria into five main categories allows for more effective analysis of operator-navigators' intuitive actions and simplifies the process of identifying such actions in real-time.

5.3. Application of the Generalized Model

Identification of Intuitive Actions: Using the generalized categories enables faster and more accurate detection of navigators' intuitive actions.

Risk Assessment: Each category is associated with certain risks, allowing for the assessment of the potential impact of intuitive actions on navigational safety.

Development of Management Strategies: Understanding the general categories helps in developing effective strategies to minimize the negative consequences of intuitive actions.

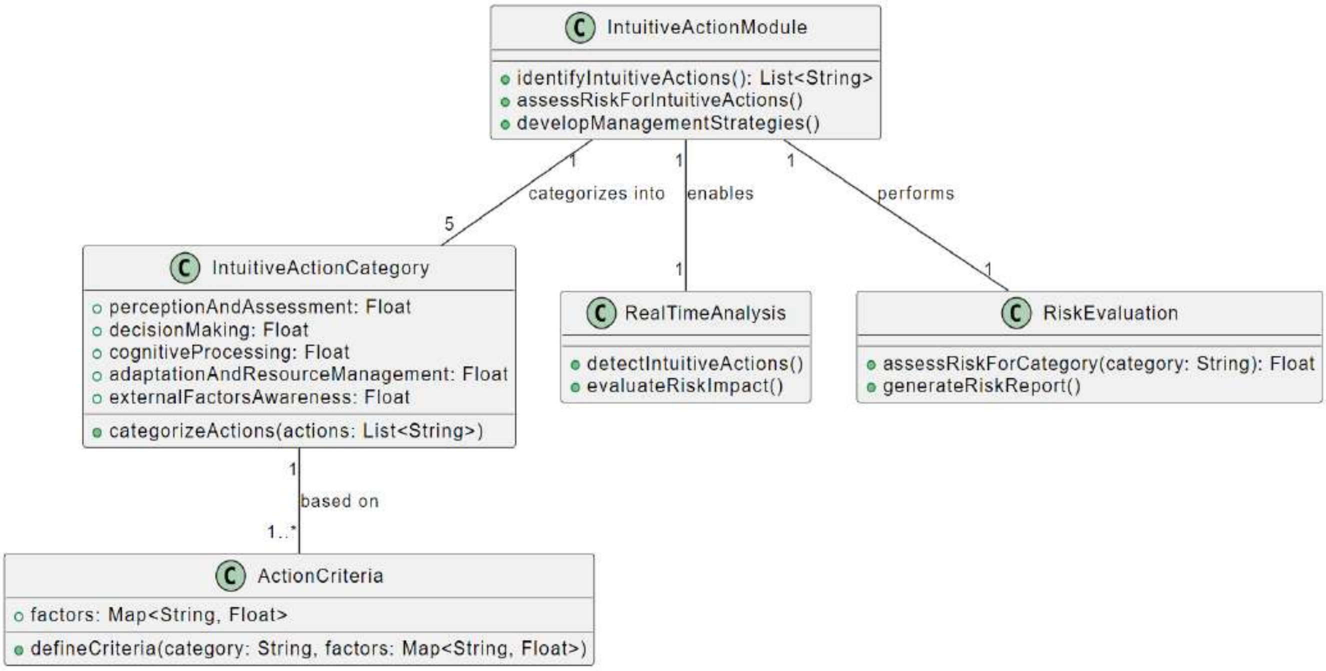

Figure 5 – Scheme of the Module for Identifying Intuitive Actions of Operator-Navigators

6. Module for Processing Navigational Data and Geolocations

The module for processing navigational data and geolocations enhances vessel safety and efficiency by integrating automated decision support systems that account for data uncertainty and incompleteness. Its objectives are to automate data collection from ECDIS, analyze and compare textual data and geolocations, visualize geographic data on interactive maps, and develop a navigator decision support system based on the processed data.

6.1. The module comprises four main components:

6.1.1. Automated image processing and text recognition (OCR) captures real-time ECDIS screenshots, preprocesses images, recognizes text using technologies like the Tesseract library, and saves data for analysis without operator intervention.

6.1.2. Analysis and comparison of textual data and geolocations involves loading and structuring data, comparing textual information between screenshots, calculating data similarity using algorithms, and analyzing geolocations by computing distances with the Haversine formula.

6.1.3. Visualization of geographic data creates interactive maps displaying the vessel's route, adds markers for specific locations and hazard zones, visualizes deviations from the planned route, and updates maps automatically using tools like the Folium library.

6.1.4. Decision support for the navigator compares current navigational data with reference templates, identifies risks, provides recommendations based on an expert action dictionary, and integrates with other modules for comprehensive analysis, utilizing machine learning algorithms to enhance recommendation accuracy.

6.2. Integration of these components ensures data integrity and consistency, speeds up data processing and analysis, and improves decision-making through a comprehensive approach.

6.3. The module results in enhanced navigational safety by timely detecting risks and reducing human errors through automation, economic efficiency by optimizing routes to reduce sailing time and costs, and improved situational awareness via interactive visualization and relevant recommendations. Implementing this module is crucial for automating data collection and analysis, integrating modern technologies into decision-making, and adapting to different conditions and navigator requirements.

Its implementation contributes to enhancing the safety and efficiency of navigation by providing: Automation of navigational data collection and analysis. Integration of modern technologies to improve the decision-making process. Ability to adapt the system to different conditions and navigator requirements.

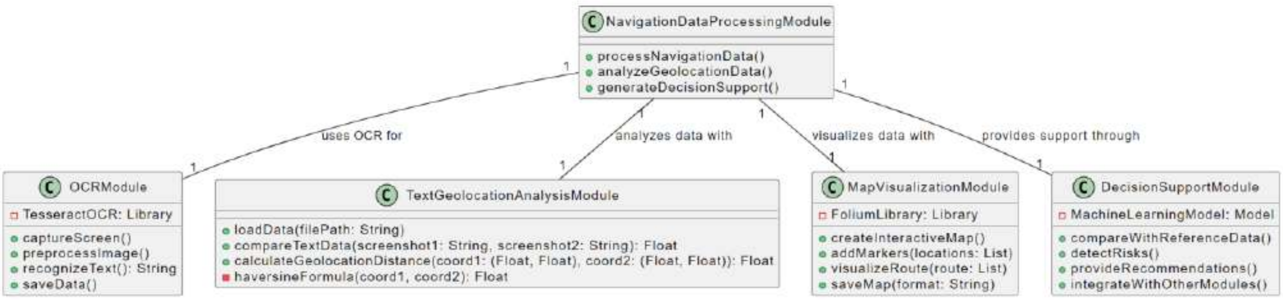

Figure 6 – Scheme of the Module for Processing Navigational Data and Geolocations

7. Module for Predicting Ship Trajectories and Risk Assessment.

Building upon the decision support system (DSS) developed earlier, integrating a ship trajectory prediction and risk assessment module is essential for enhancing maritime safety. This module anticipates potential navigational scenarios and identifies threats in a timely manner, providing navigators with relevant recommendations for optimal decision-making.

7.1. It closely connects with other DSS components by using data from navigational processing modules as input for prediction models, and visualizations from Module 6 to display predicted trajectories and risk zones.

7.2. Machine learning algorithms, such as multilayer neural networks, predict future ship positions by adapting to specific sailing conditions and ship characteristics. The module analyzes these predicted trajectories to assess risks of collisions or proximity to hazardous zones, considering uncertainties and human factors, and classifies risks to prioritize actions. It integrates with the DSS by providing prediction results and recommendations, which are visualized on interactive maps.

7.3. This enhances maritime safety by timely identifying potential hazards, improves decision-making efficiency with accurate recommendations, reduces navigator workload by automating complex analyses, and optimizes routes by considering predicted conditions and risks. Integrating this module ensures a comprehensive approach to navigational analysis, seamless data exchange, and adaptability to various sailing conditions. Combined with previous modules, it contributes to creating an effective DSS that enhances maritime safety and efficiency by reducing risks and optimizing navigation processes.

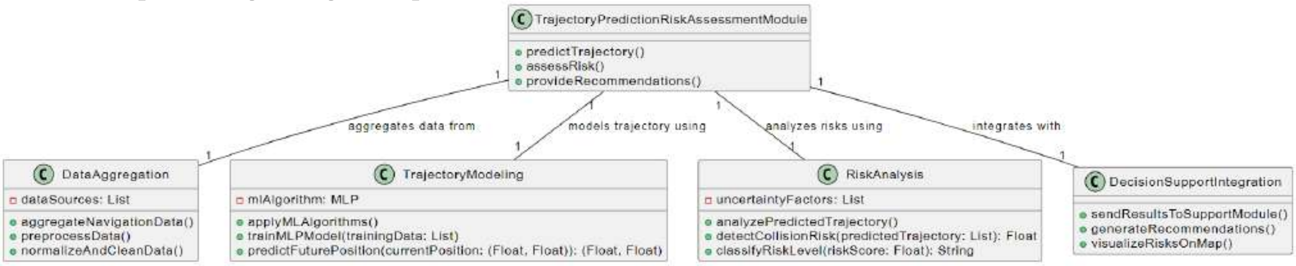

Figure 7 – Scheme of the Module for Predicting Ship Trajectories and Their Risks

Developing the module for predicting ship trajectories and risk assessment, in conjunction with the previous six modules, allows for the creation of a comprehensive and effective decision support system for the navigator. This contributes to enhancing the safety and efficiency of maritime navigation by reducing risks and optimizing the navigation process.

Conclusion. A comprehensive navigator qualification model for automated ship control was developed, incorporating technical, cognitive, and behavioral aspects to enhance real-time decision-making and ensure safe navigation in dynamic environments. Key research tasks accomplished include analyzing modern qualification assessment methods – such as fuzzy logic, neural networks, and artificial intelligence – to integrate technical and behavioral aspects effectively.

The Navigator Qualification Model (NQM) was structured with modules for input data and navigation parameters, hazard level assessment using fuzzy logic, navigator qualification identification using neural networks, cognitive analysis of intuitive actions, navigational data and geolocation processing, and ship trajectory forecasting and decision-making. These modules collectively provide a systematic assessment of the navigator's professional competencies.

The model adapts to external factors and changing navigation conditions by using a mathematical risk model that considers variables like speed, under-keel clearance, and weather conditions. It identifies critical competencies for safe navigation and incorporates the human factor in risk assessments through the analysis of intuitive actions.

Potential applications of the model include enhancing maritime safety by timely detecting risks and providing minimization recommendations, personalizing navigator training by identifying competency gaps, seamless integration with existing navigation systems without significant infrastructure changes, and adaptability to varying conditions and individual navigator characteristics.

Future research prospects involve expanding the training database to improve model accuracy and reliability, implementing additional artificial intelligence elements for more precise predictions and adaptability, and investigating the impact of the navigator's psychophysiological state – such as stress and fatigue – on decision-making to further refine the model.

In summary, the research objective was achieved by creating a comprehensive qualification model that combines fuzzy logic, neural networks, and artificial intelligence. This model systematically assesses navigators' professional qualifications, crucial for safe and efficient navigation. Implementing this model in maritime practice will enhance safety levels and optimize ship management processes.

REFERENCES

1. Pham, Duc-Anh & Han, Seung-Hun (2023). Designing a Ship Autopilot System for Operation in a Disturbed Environment Using the Adaptive Neural Fuzzy Inference System. Journal of Marine Science and Engineering. 11. 1262. 10.3390/jmse11071262.

2. Liu, Wenwen & Liu, Yuanchang & Gunawan, Bryan & Bucknall, Richard (2020). Practical Moving Target Detection in Maritime Environments Using Fuzzy Multi-sensor Data Fusion. International Journal of Fuzzy Systems. 23. 10.1007/s40815-020-00963-1.

3. Du, Zhixiu (2024). A Risk Assessment Model for Navigation Safety of Maritime Aquaculture Platform Based on AIS Ship Trajectory. Journal of Electrical Systems. 20. 116–123. 10.52783/jes.2364.

4. Devikala, S. (2024). Development of Fuzzy Logic Controller in Automatic Vehicle Navigation using IoT. Journal of Electrical Systems. 20. 114–121. 10.52783/jes.1254.

5. Gül, Muhammet & Ak, Muhammet Fatih (2022). Occupational Risk Assessment for Flight Schools: A 3,4-Quasirung Fuzzy Multi-Criteria Decision Making-Based Approach. Sustainability. 14. 9373. 10.3390/su14159373.

6. Wang, Shaobo & Zou, Yiyang & Wang, Xiaohui (2024). An Intelligent Decision-Making Approach for Multi-Ship Traffic Conflict Mitigation from the Perspective of Maritime Surveillance. Journal of Marine Science and Engineering. 12. 1719. 10.3390/jmse12101719.

7. Aylward, Katie & Weber, Reto & Lundh, Monica & MacKinnon, Scott & Dahlman, Joakim (2022). Navigators' views of a collision avoidance decision support system for maritime navigation. Journal of Navigation. 75. 1–14. 10.1017/S0373463322000510.

8. Wang, Yuqing & Chen, Xinqiang & Wu, Yuzhen & Zhao, Jiansen & Postolache, Octavian & Liu, Shuhao (2024). Visual Navigation Systems for Maritime Smart Ships: A Survey. Journal of Marine Science and Engineering. 12. 1781. 10.3390/jmse12101781.

9. Li, Wei & Chen, Weijiong & Guo, Yunlong & Hu, Shenping & Xi, Yongtao & Wu, Jianjun (2024). Risk Performance Analysis on Navigation of MASS via a Hybrid Framework of STPA and HMM: Evidence from the Human–Machine Co-Driving Mode. Journal of Marine Science and Engineering. 12. 1129. 10.3390/jmse12071129.

10. Houweling, Koen & Mallam, Steven & van de Merwe, Koen & Nordby, Kjetil (2023). An Approach for Measuring The Effects of Augmented Reality on Human Performance in Maritime Navigation. Proceedings of the Human Factors and Ergonomics Society Annual Meeting. 67. 10.1177/21695067231193647.

11. Mohamed, Eslam & Hosny, Moustafa (2024). Enhancing Safety of Navigation with ECDIS Standardization and S-Mode Adoption. Maritime Research and Technology. 3. 117. 10.21622/MRT.2024.03.2.932.

12. Lee, Changui & Seojeong, Lee (2024). A Risk Identification Method for Ensuring AI-Integrated System Safety for Remotely Controlled Ships with Onboard Seafarers. Journal of Marine Science and Engineering. 12. 1778. 10.3390/jmse12101778.

13. Lei, Jinyu & Sun, Yuan & Wu, Yong & Zheng, Fujin & He, Wei & Liu, Xinglong (2024). Association of AIS and Radar Data in Intelligent Navigation in Inland Waterways Based on Trajectory Characteristics. Journal of Marine Science and Engineering. 12. 890. 10.3390/jmse12060890.

14. Car, Maro & Vujicic, Srdjan & Žuškin, Srđan & Brčić, David (2019). Human Machine Interface: Interaction of OOWs with the ECDIS system. Conference: 1st International Conference of Maritime Science & Technology – Naše More 2019.

15. Medic, Dario & Bošnjak, Rino & Bukljaš, Mihaela & Vukša, Srđan (2021). Research Study and the Model for Improving the Safety of Navigation when Using the AIS. TransNav the International Journal on Marine Navigation and Safety of Sea Transportation. 15. 577. 10.12716/1001.15.03.10.

16. Liu, Tian & MA, Jianwen (2022). Ship Navigation Behavior Prediction based on AIS Data. IEEE Access. 10. 1–1. 10.1109/ACCESS.2022.3172308.

17. Jiang, Zhiqiang & Zhang, Lingyu & Li, Weijia (2024). A machine vision method for the evaluation of ship-to-ship collision risk. Heliyon. 10. e25105. 10.1016/j.heliyon.2024.e25105.

18. Vukić, Đurđica & Candrlic, Sanja & Poščić, Patrizia (2020). COMPARATIVE OVERVIEW OF ADAPTIVE ASSESSMENT ACTIVITY IN OPEN SOURCE LMS: DATA MODEL PERSPECTIVE. 4944–4954. 10.21125/inted.2020.1356.

19. Moon, Kibum & Kim, Jinwon & Lee, Jinsook (2021). Early Prediction Model of Student Performance Based on Deep Neural Network Using Massive LMS Log Data. The Journal of the Korea Contents Association. 21. 1–10. 10.5392/JKCA.2021.21.10.001.

20. Putra, Bagas & Soeprijanto, & Daryanto (2024). Evaluation of the Utilization of the Learning Management System (LMS) Using the CIPP Model. Global Synthesis in Education Journal. 1. 19-27. 10.61667/dp8q3757.

21. Elov, Botir & Rasulovna, Jamoldinova & Mastura, Primova & Khusainova, Zilola & Raxmatilloyevich, Aloyev & O'g'li, Xudayberganov (2024). The Stages of Creation of LMS Model.

22. Liu, Dongqin & Zheng, Zhongyi & Liu, Zihao (2024). Research on Dynamic Quaternion Ship Domain Model in Open Water Based on AIS Data and Navigator State. Journal of Marine Science and Engineering. 12. 516. 10.3390/jmse12030516.

23. Okechukwu, Ogochukwu & Amaechi, Eziechina & George, Onyemachi & Isaac, Onuwa (2024). Enhanced Text Recognition in Images Using Tesseract OCR within the Laravel Framework. Asian Journal of Research in Computer Science. 17. 58–69. 10.9734/ajrcos/2024/v17i9499.

24. Manjunath, Akanksh & Nayak, Manjunath & Nishith, Santhanam & Pandit, Satish & Sunkad, Shreyas & Deenadhayalan, Pratiba & Gangadhara, Shobha (2023). Automated invoice data extraction using image processing. IAES International Journal of Artificial Intelligence (IJ-AI). 12. 514. 10.11591/ijai.v12.i2.pp514–521.

25. Sumana, K. R. (2024). Optimized OCR Data Extraction Using Custom-Trained NLP-NER Models for Enhanced Image Analysis. Journal of Emerging Technologies and Innovative Research. 11. 159–162.

26. Ujkani, Arbresh & Hohnrath, Pascal & Grundmann, Robert & Burmeister, Hans-Christoph (2024). Enhancing Maritime Navigation with Mixed Reality: Assessing Remote Pilotage Concepts and Technologies by In Situ Testing. Journal of Marine Science and Engineering. 12. 1084. 10.3390/jmse12071084.

27. Martes, Liliana (2020). Best Practices in Competency-based Education in Maritime and Inland Navigation. TransNav, the International Journal on Marine Navigation and Safety of Sea Transportation. 14. 557–562. 10.12716/1001.14.03.06.

28. Victoria Ponomaryova, Pavlo Nosov (2023). Method of automated identi-fication of qualification parameters for marine operators under risk conditions // Naukovyi visnyk Khersonskoi derzhavnoi morskoi akademii (Avtomatyzatsiia ta kompiuterno-intehrovani tekhnolohii): naukovyi zhurnal. – Kherson: Khersonska derzhavna morska akademiia, № 26–27 (2023). S. 144–165.

29. Ponomaryova, V., Nosov, P., Ben, A., Popovych, I., Prokopchuk, Y., Mamenko, P., Dudchenko, S., Appazov, E., & Sokol, I. (2024). Devising an approach for the automated restoration of shipmaster's navigational qualification parameters under risk conditions. Eastern-European Journal of Enterprise Technologies, 1(3 (127), 6–26. https://doi.org/10.15587/1729-4061.2024.296955.

30. Victoria Ponomaryova (2024). Method of decision support for navigators in automated vessel traffic safety control based on ecdis data // Naukovyi visnyk Khersonskoi derzhavnoi morskoi akademii (Avtomatyzatsiia ta kompiuterno-intehrovani tekhnolohii): naukovyi zhurnal. Kherson: Khersonska derzhavna morska akademiia, № 1 (28), 2024. S. 22–40.

Пономарьова В., Носов П. РОЗРОБКА КВАЛІФІКАЦІЙНОЇ МОДЕЛІ СУДНОВОДІЯ ДЛЯ ЗАДАЧ АВТОМАТИЗОВАНОГО КЕРУВАННЯ СУДНОМ

Дослідження спрямоване на розробку комплексної кваліфікаційної моделі штурманів в автоматизованому управлінні судном, яка оцінює технічну, когнітивну та поведінкову компетентність для підвищення ефективності прийняття рішень у реальному часі в умовах змінного навігаційного середовища.

Головним викликом є інтеграція передових технологій, таких як штучний інтелект та нечітка логіка, для точного моніторингу ризиків, що виникають через людський фактор.

Методологія включає створення моделі, яка оцінює компетенції штурмана шляхом інтеграції різних аспектів. Дані з ECDIS та інших сенсорів обробляються у вектор ознак. Алгоритм Мамдані агрегує нечіткі правила, що визначають кваліфікаційні параметри, а нейронні мережі моделюють складні взаємозв'язки. Модель використовує нечіткі функції належності для оцінки ризиків з урахуванням швидкості, глибини під кілем, погодних умов та ймовірності зіткнення.

Результати показують, що модель вчасно виявляє потенційні ризики та автоматизує процес прийняття рішень, зменшуючи навантаження на штурмана в складних умовах. Вона ефективно прогнозує траєкторію судна, ідентифікує ризикові зони та надає рекомендації щодо безпеки.

Практично це підвищує безпеку мореплавства через персоналізовану оцінку штурмана. Інтеграція з існуючими системами, такими як ECDIS, пропонує гнучкість без значних змін інфраструктури. Система індивідуалізує рекомендації, знижуючи ризик аварій та покращуючи ефективність підготовки. Майбутні дослідження включають розширення бази даних для підготовки, удосконалення алгоритмів та вивчення впливу психофізіологічного стану штурмана на ефективність управління судном.

Ключові слова: *кермове управління; оптимізація процесів керування; модуль автоматичного керування; аварійні ситуації; транспортні потоки; інформаційна підтримка; Safety Depth; ECDIS; маневрування у стиснених водах; система розпізнавання.*

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