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DEVISING AN APPROACH FOR THE AUTOMATED RESTORATION OF SHIPMASTER'S NAVIGATIONAL QUALIFICATION PARAMETERS UNDER RISK CONDITIONS

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The object of this study is the safety control system of ship management, by identifying and restoring the qualification parameters of shipmasters in critical situations.

The task solved in the study is the timely determination of an insufficient level of qualification for the performance of certain operations in controlling the movement of the ship, by applying a formal-logical model of detecting the intuitive actions of the operator-shipmaster and gradually restoring his/her qualification parameters using the devised method.

The stages of development and the formal-logical structure of the model and method in terms of cognitive automation were described in detail as the study results. It was possible to ensure early detection of risks when controlling the movement of the ship in 56 % of cases, during a laboratory experiment on simulators, which in 24 % of cases turned out to be particularly dangerous.

The interpretation of the results involved algorithmizing complex and formalized data on the actions of operators and the application of the method of restoring their qualification parameters, which allowed a comprehensive approach to safety management.

The distinguishing features of the findings were to predict the level of danger by simulating maritime operations with input navigational and individual conditions. This made it possible to improve the effectiveness of operations to 89 %, reduce the phenomenon of loss of control over the course to 32 %, reduce critical situations to 7 % and the cost of resources.

The scope and conditions of practical use involve a comprehensive assessment of external and internal influences on the level of danger, delay in decision-making by operators, as well as sailing conditions. The simulation results could be used to devise strategies for planning maneuvers, predicting risks, and developing maritime security systems

Keywords: cognitive automation, qualification parameters, navigation risks, sea transport, human factor

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1. Introduction

The modern world is facing unprecedented challenges in the field of maritime transport, especially given the high requirements for qualification parameters of shipmasters. Under conditions of ever-increasing risk, the efficiency and safety of shipping directly depend on the qualification of shipmasters, which needs constant renewal and improvement.

In this context, the issue of constant monitoring of these parameters and, accordingly, the development of an approach for the automated restoration of qualification parameters of shipmasters, which creates new opportunities for improving the safety and efficiency of maritime transport, is relevant.

Considering the complexity of the monitoring processes, it is planned to devise a comprehensive method for the automated restoration of qualification parameters of shipmasters, which will allow timely detection and correction of potential deficiencies that directly affect the safety of shipping. In this sense, the study should be based on the analysis of modern trends in maritime transport, as well as take into account the specificity of the work of shipmasters under risky conditions. The complexity and multifacetedness of this problem require detailing when considering both theoretical and practical aspects of the approach, which includes the construction of the appropriate logic of algorithms, data analysis, and experimental research.

The main task of the study in this case should include the development of an appropriate methodology for the analysis and identification of qualification parameters, the construction of a model for determining the non-standard behavior of shipmasters, which will indicate the loss of qualification parameters. Therefore, in this study, we assume that the human factor plays a decisive role in ensuring the safety of navigation and this directly affects the focus of developing practical recommendations and optimizing navigational safety.

The results of our study will predict changes in the practice of automated management of maritime transport safety and could be a significant contribution to the development of technologies for retraining shipmasters.

2. Literature review and problem statement

In order to analyze existing approaches in terms of the problem outlined above, we shall consider a number of studies relevant to the class of tasks mentioned above.

Thus, in work [1], attention is focused on the use of machine learning (ML) to predict academic success in maritime education. Various ML models are used, including logistic regression, decision trees, artificial neural networks, support vector method, Bayesian networks, gradient boosting machine, and k-nearest neighbors. Special emphasis is on automated machine learning, AutoML (Automated Machine Learning) for efficient and less resource-intensive model building.

Emphasis is on the importance of ML in early identification of at-risk students, which is key to timely intervention and support. The question of the importance of qualification data or their recovery is not clearly discussed. However, the role of human intervention and critical thinking in the use of automated systems in education are recognized, which may indirectly indicate the value of qualification data. Risks are not directly addressed, but the need for human supervision indicates an awareness of the limitations and potential problems of automated systems.

In paper [2], attention is paid to the development of a model for assessing the suitability of using cognitive automation (CA) in various scenarios. The main aspects of the research include the use of cognitive automation in the form of machine learning and artificial intelligence algorithms to optimize and automate processes in various industries. The CA evaluation model has four dimensions: data requirements, cognitive requirements, interaction requirements, and transparency requirements.

The cited article emphasizes the importance of high-quality and relevant data for the successful application of CA. Attention is focused on the need for systematic data collection and analysis before the implementation of CA. Also discussed are the risks associated with the implementation of cognitive automation, such as strategic, sourcing, instrumental, and change management risks.

However, despite the detailed analysis and high scientific level of the document, it can be noted that the practical application of the proposed model may be limited as it requires a significant level of technical understanding and resources for analysis and implementation. It is also important to note that the successful implementation of CA depends on the context of the organization and the specificity of the industry, and therefore does not take into account the human factor, which requires additional adaptations of the model.

Study [3] analyzes the cognitive stability of pilots in digital flights and the effects of computer information and automation. The model of crew resource management, CRM (Crew Resource Management) and threat and error management, TEM (Threat and Error Management), supplemented with aspects of cognitive stability, is used. The focus is on the impact of digital systems on pilot cognitive performance, including information overload and impaired situational awareness. The importance of qualification data and their recovery is analyzed, the risks associated with digital systems and their impact on flight safety are considered. At the same time, all the latest technological trends are not taken into account, and the experience and skills of pilots are not considered, which can affect the effectiveness of using digital systems and cognitive stability.

In paper [4], interactions between safety management systems SMS (Safety Management System) and cyber security CSMS (Cybersecurity Management System) for highly automated vehicles HAD (Highly Automated Driving) were analyzed.

The main focus is on the development of SMS and CSMS interfaces using risk assessment models. An analysis of the impact of cyber threats on the safety of the operation of vehicles was performed.

Implementation of surveys and questionnaires to collect data from security and cyber security experts.

The cited article emphasizes the importance of qualification data for the development of secure systems but does not mention the need to restore it. Risks related to cyber security and operational security are considered.

However, the study may be limited by using data from only a narrow range of experts, which may not reflect the broader picture of the impact of these factors across organizations or industries.

Paper [5] discusses the stages of development and evaluation of an electronic learning tool designed to train users to use automated vehicles. The main technical aspects include the development of educational content, integration with visual and multimedia elements, the use of various programs for graphics and audio-video processing. The cited paper emphasizes the importance of qualification data for the creation of effective training programs but does not focus on the recovery of this data. Risks are not considered in detail.

Also, the materials contain limited information on the impact of artificial intelligence and machine learning technologies on the effectiveness of educational tools, which may be important for a deeper understanding of the interaction between humans and automated systems.

Technical tools including Bayesian networks and the failure tree method, combined to assess risks and their causes, were analyzed in [6]. The theory of fuzzy sets is used to determine the probabilities of main events. The study emphasizes the importance of qualification data, especially in the context of maritime transport risk assessment.

However, the study may be limited by the lack of consideration of different maritime transport contexts and possible differences in risks on different routes. It is important to consider these aspects for a more universal application of the results.

Paper [7] examines the impact of navigation automation and the level of mental workload on awareness of the maritime situation. Bayesian networks and the failure tree method are used for analysis. The importance of qualification data is emphasized in the context of forecasting accuracy and risk analysis. However, the document does not mention the need to restore this data. At the same time, the risks associated with the automation of navigation are considered in detail.

However, the study may suffer from a lack of realistic simulations of sea conditions and crew behavior, limiting the applicability of its findings to actual maritime operations.

In turn, work [8] analyzed the impact of artificial intelligence and machine learning technologies on business processes. The main emphasis is on machine learning as a key element of cognitive automation, which allows automating knowledge and service work. The importance of qualification data for accurate analysis and forecasting is emphasized but data recovery is not addressed. The paper discusses the risks associated with the implementation of cognitive automation, especially regarding the unpredictability of the results.

In addition, the document does not focus on the practical application of cognitive automation in various industries, which could help better understand how these technologies could be integrated into specific processes.

Another perspective, in [9], includes the development of a model based on fuzzy logic for solving the problems of avoiding collisions in maritime navigation. The techniques and models used focus on the analysis of the dynamic parameters of the marine vehicle to determine the course change. The paper emphasizes the importance of good quality and accurate data for modeling collision avoidance situations but does not discuss data recovery. The risks associated with navigation and collision avoidance are considered in the context of the accuracy and reliability of the decisions made.

However, the research may have limitations due to its dependence on the presented data and specific situations, which in turn depend on the factor of the human operator of the vessel.

In work [10], attention is focused on the use of FPGA (Field-Programmable Gate Array) as an integrated circuit that can be programmed after its production and to accelerate applications of convolutional neural networks. Key technical features included algorithm-hardware design and optimization of SGCNet (Shift Gaussian Convolution Network) for easy human re-identification. It uses 1x1 kernel convolution and displacement instead of spatial convolution. The importance of qualifying data is emphasized but data recovery is not mentioned. The considered risks are related to the accuracy of the network and the ease of implementation of the equipment. However, the document could have better covered the applicability of SGCNet in a variety of practical scenarios, not just in the specific context of human re-identification.

Tasks on active maritime safety training were also considered [11], using virtual training scenarios. Key technical aspects include the concept and development of a virtual training vessel based on the principles of active learning and the use of open technologies such as Godot and Blender. The paper emphasizes the importance of qualification data for realistic modeling but does not discuss their recovery. The risks associated with active learning are considered.

However, the document does not fully take into account the specificity of real conditions of maritime operations, which may limit the practical application of training scenarios.

Another perspective, in paper [12], focuses on the development of a methodology for assessing the safety of autonomous vehicles. The main technical aspects include SCF (Safety Case Framework), SMS (Safety Management System), scenario-based testing methods. The paper emphasizes the importance of qualification data for the development of secure systems. Risks are assessed based on safety data and the use of this data in the Safety Case Framework (SCF).

However, not enough attention has been paid to the analysis of the impact of these methodologies on different types of vehicles and their specific operating conditions, which is critical for the development of universal safety standards.

In [13], the leading technologies of integration of BCI (Brain Computer Interface) brain-computer interface technology into automation systems are studied. BCIs are used to control various devices in the environment through neural signals. The use of hardware such as Emotiv EPOC+ (making it possible to detect cognitive states, emotions, focus of attention and other mental states of the user) and software for collecting and processing brain signals is considered. The importance of qualification data and its analysis is emphasized but its recovery is not discussed. Possible risks and challenges associated with the use of BCI in automation are considered.

However, potential problems with the accuracy and reliability of BCI technologies, which may affect the effectiveness of their implementation under real conditions, are not taken into account.

3. The aim and objectives of the study

The purpose of our study is to devise a comprehensive method for the automated restoration of qualification parameters of shipmasters under conditions of high risk and difficult navigation situations. The proposed approach could make it possible to build a ship management safety control system based on identification data and analysis of cognitive processes that affect the efficiency and safety of maritime transport from the operator-shipmaster.

To achieve the goal, the following tasks were set:

– to construct a model for identifying the intuitive actions of operators-shipmasters in critical situations when controlling the movement of a vessel under difficult sailing conditions;

– to devise a formal and logical method of restoration of qualification parameters of a shipmaster under conditions of foreseeable navigational risks and real-time mode;

– to develop a set of data processing schemes by categories to provide for a method of restoring the qualification parameters of a shipmaster, which would allow a comprehensive impact on the reduction of shipping risks;

– to build a mathematical model for the analysis of changes in the level of danger in navigation, taking into account the time of restoration of the shipmaster's qualification parameters, by integrating data from navigation systems and data on the time delay in decision-making.

4. The study materials and methods

The object of our study is the process of restoring the qualification parameters of shipmasters under the difficult conditions of keeping a navigational watch.

Taking into account the a priori mathematical uncertainty of many processes of human intellectual activity, it is difficult to talk about the reasons due to which non-standard behavior of a shipmaster is observed, which indicates the fact of a partial loss of qualification parameters. Taking into account the complexity of the processes on which the level of safety of the operator's actions depends, it is necessary to determine the boundary between his/her rationality in the decisions s/he makes and his/her intuitive behavior, which definitely indicates risks.

The task of determining such a limit for the purpose of tracking the rationality of actions of the operator-shipmaster involves a non-trivial and complex problem, especially in real time, when keeping a navigational watch. In this task, it is necessary to devise a logical-formal approach to determine the states of transition from rational to intuitive to develop a timely response to support decision-making and safe navigation.

A similar task is considered, for example, in [14], whose authors define human rationality as reasoning and decision-making according to cognitive strategies that make the best use of limited mental resources.

Also, in Kahneman's theory of two systems, it is assumed that decision-making is based on two cognitive systems: one automatic, intuitive, and mainly unconscious (System 1), and the other – reflexive, rational, and fully conscious (System 2) [15]. Thus, there is a task in determining the identifiers of the intuitive (dangerous) behavior phase of a shipmaster based on implicit signs that are difficult to track through visual observation by other members of the watch service. Having determined the time range of the activation of the dangerous phase, an opportunity will appear in synchronization with the route zones, current operations, expected actions, which indicates the specific, lost component elements of the qualification parameters of the operator-shipmaster.

So, first of all, it is necessary to formally define those actions that make it possible to separate intuitive behavior from conscious behavior [16]. In the case of intuitive behavior of the operator, when the experience is too little, or the situation is unknown, the knowledge recovery mechanism should work. In another case, NDM (Naturalistic Decision Making), (T-Task) – unconscious decision-making operators are activated under conditions of uncertainty, which leads to the presence of a chaotic «Dark Solution» phase.

For the purpose of a more in-depth analysis of the specified risks, data was collected during work with simulators of ship movement control from the educational component «Navigation and sailing directions» – the ECDIS (Electronic Chart Display and Information System) module in the certified training center Anglo-Eastern Ukraine, Odesa, during October-November 2023 (Fig. 1).

According to the results of the processed data, the hypothesis was confirmed that in moments of insufficient qualification parameters, cadets switch to models of intuitive behavior, which depends on their individual characteristics and previous experience. Risks in the organization of human-machine interaction when using automated ship motion control systems were identified in 56 % of cases during the laboratory experiment.

a

b

Fig. 1. The use of the Transas NS 5000 simulator in data analysis: *a* – downloading the divergence scenario; *b* – creation of critical situations

It was determined that in such cases, in 63 % of navigation situations there is a significant deviation from the given course of the vessel, in 37 % it led to a decrease in speed, which affects the overall traffic intensity. In turn, the state of intuitive behavior of cadets, with clear signs of loss of certain qualification parameters, in 24 % of cases led to collisions with oncoming vessels and grounding, which is defined as a catastrophic situation.

Given the above, experimental data were collected and analyzed in order to delve deeper into the problem of identifying risks and finding approaches to their leveling. The data collected during a voyage in October-November 2023 in difficult navigation areas in the North Sea area made it possible to determine the elements of the intuitive behavior of operator-shipmasters.

5. Simulation results for the automated restoration of the qualification parameters of a shipmaster under the conditions of navigational risks

5. 1. Construction of a model for identifying the intuitive actions of operator-shipmasters in critical situations

So, based on the tasks of our research, the structure of a formal model of identification of intuitive actions of operator-shipmasters is proposed, consisting of 15 categories, in which each category is represented by a formal description, a manifestation of the shipmaster, an identification criterion, and the principal factor:

1. Perception and assessment of the situation.

Formal description (1):

$$f/\mu : z/Z_\alpha ?_{int} 1 \rightarrow z/Z_\alpha ?2, \qquad (1)$$

where z is the current state of a shipmaster, Z_α ?1, z/Z_α ?2 are the states before and after the intuitive assessment.

Manifestation: an unconscious sense of danger, manifested in the neglect of the process of studying the coastal area before approaching it. Especially when the situation requires sailors to have a high level of attentiveness and perception of details in order to correctly assess the danger (Fig. 2).

Criterion: too quick awareness of changes.

Factor: $Z_\alpha ?_{int}$ – unexpected quick intuitive perception of the situation.

2. Dynamics of intuition and choice of actions.

Formal description (2):

$$f/\mu : \neg\tau/T \rightarrow \tau/T_{int}, \qquad (2)$$

where τ is the current target state, T is the set of possible states.

Manifestation: decision «by feeling», which causes neglecting the analysis of possible risks when choosing the safest routes, choosing quick decisions based on intuition.

Criterion: a sudden feeling of «correctness of actions».

Factor: τ/T_{int} is an intuitive choice that is not provided by the instructions.

3. Cognitive processes.

Formal description (3):

$$Gv(\tau) = Cog(aPa) \rightarrow eCog(bPb)\tau[Context], \qquad (3)$$

where τ is the context of actions, Cog is a cognitive function, Pa, Pb are parameters related to elements a and b.

Manifestation: unexpected associative connections, which violates the algorithms of using navigation tools (GPS (Global Positioning System), electronic maps, ECDIS) for accurate determination of the vessel's location, as well as visual and radar observations (Fig. 3, a, b).

Criterion: instant understanding of complex information.

Factor: $Cog_{int}(a,b)$ – intuitive understanding of the sequence of actions in complex operations.

4. General transformation (adaptation to changes).

Formal description (4):

$$Gv\Xi(\tau) = f/\mu : \tau \rightarrow e\tau'[Context]\Xi \in \Xi, \qquad (4)$$

where Ξ is the set of possible changes, τ' is the new context after adaptation.

Manifestation: intuitive response to changes, which leads to unexpected flexibility to changes in navigation plans in response to unforeseen conditions or new information [17] that is discovered during navigation.

Criterion: Fast adaptation without analysis.

Factor: Ξ_{int} – intuitive adaptation to an unknown set of navigation data.

Fig. 2. Perception and assessment of the situation (determining the time of analysis)

a *b*

Fig. 3. Unexpected associative connections and understanding of complex information
a — GPS data; *b* — Navtex data (NAVigational TEleX, international automated warning system) corresponding to GPS

5. Complex model of behavior.

Formal description:

$$Gv(\tau)=a\{Context\}a\{Affordance\}a\{Contrfactuals\}\\ a\{Metaphor\}a\{Emotion\}a\{g/\mu\}a\{LAoT\}a\rightarrow\\ \rightarrow\{h/\mu(e)\}b\{Context\}b\{Affordance\}b\{Contrfactuals\}\\ b\{Metaphor\}b\{Emotion\}b\{g/\mu\}b\{LAoT\}b\tau,$$

where *LAoT* are tools (of local «time vectors») or technologies used intuitively.

Manifestation: subconscious management of several tasks, and as a result, poor coordination of various components of sailing, including navigation, watchkeeping, maneuverability of the vessel, and speed control under difficult conditions.

Criterion: multitasking without conscious focus.

Factor: $LAoT_{int}$ – intuitive synchronous actions by tools and equipment.

6. Processing of complex events and decision-making in critical situations.

Formal description (5):

$$Ev\uparrow \equiv <\tau\,|\,xp\varepsilon>\uparrow \equiv <\tau g/\mu\tau pg/\mu p\varepsilon g/\mu\varepsilon > g/\mu Ev\uparrow, \qquad (5)$$

where *Ev* is a specific event or situation, τ, *x, p,* ε are parameters affecting the reaction.

Manifestation: intuitive decision-making in critical situations (Fig. 4), which is observed in insufficient time analysis of critical situations, such as the probability of collision of ships, etc.

Criterion: quick decision (change of speed/course) without lengthy analysis.

Factor: Ev_{int} – intuitive response to events.

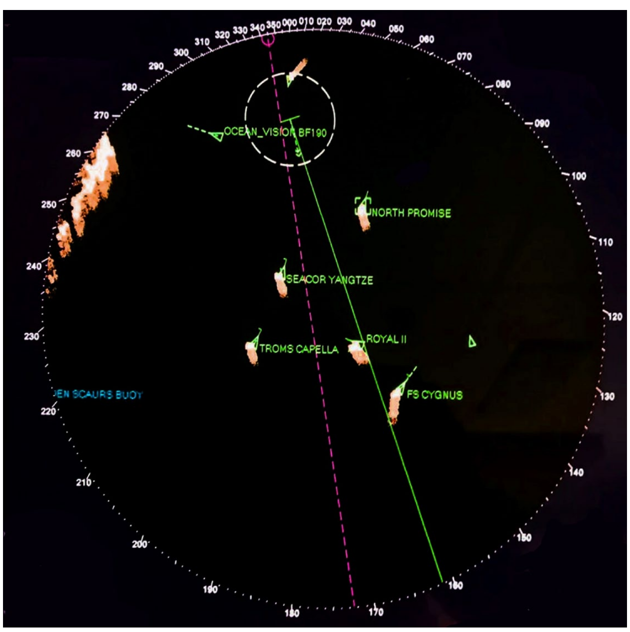

Fig. 4. Intuitive decision-making in multifactorial critical situations

7. Search for rewards and effects.

Formal description (6):

$$Ev\uparrow \infty Ev \,\&\, Evp\uparrow[Context]\{Rewards\}\{Effects\}, \qquad (6)$$

where *Rewards, Effects* are potential rewards and effects from the shipmaster's actions.

Manifestation: gut feeling of the «right» maneuver or action, namely insufficient risk assessment and determination of safe actions, including control of vessel speed and maneuvers.

Criterion: intuitive determination of the safest actions.

Factor: $Rewards_{int}$, $Effects_{int}$ – intuitive perception of rewards and consequences [18].

8. Serendīpity and intuition.

Formal description (7):

$$\forall Ev|\rightarrow \max <IBCSL> Ev|\rightarrow \max Idea, \qquad (7)$$

where *IBCSL* is an information context, *Idea* is an idea or solution.

Manifestation: an unexpected decision or action based on experience and observation rather than an analysis of the requirements of maritime organizations to prevent potential hazards.

Criterion: a sudden «correct» decision for no apparent reason.

Factor: $Idea_{int}$ – intuitive generation of ideas.

9. Search for resources and synthesis of time.

Formal description (8):

$$\begin{bmatrix} Resource- \\ -Search \end{bmatrix} f \begin{bmatrix} Time- \\ -Synthesis \end{bmatrix} f/\mu[HPP]\,f/\mu[Context], \qquad (8)$$

where μ is the function/mechanism used to determine resource and time usage.

Manifestation: an intuitive sense of time when using resources, manifested during the operation of navigation equipment.

Criterion: efficient use of resources and time without detailed planning.

Factor: $Resource{-}Search_{int}$, $Time{-}Synthesis_{int}$ – intuitive resource search and time synthesis.

10. World events.

Formal description (9):

$$Ev: WorldEv\uparrow : WorldEv\uparrow, \qquad (9)$$

where *WorldEv* are global events or changes affecting navigation.

Manifestation: a subconscious understanding of international standards [19], which causes the neglect of established navigational practices in decisions related to the safety of navigation.

Criterion: adaptation to global navigation practices.

Factor: $WorldEv_{int}$ – intuitive perception of world events.

11. Time display.

Formal description (10):

$$\begin{bmatrix} Start- \\ Mid- \\ End \end{bmatrix} f/\mu \begin{bmatrix} Past- \\ extendedNow- \\ Future \end{bmatrix}, \qquad (10)$$

where [*Start*], [*Mid*], [*End*] are different phases of the time period, [*Past*], [*Now*], [*Future*] are time categories.

Manifestation: intuitive determination of the optimal time for actions, which indicates a lack of planning of navigational maneuvers and actions in accordance with time constraints and requirements.

Criterion: spontaneous perception of time frames for performing actions.

Factor: $Time_{int}$ – intuitive reflection of time.

12. Complex images and events.

Formal description:

$$[Complex\ images\ chemas] f/\mu [Images\ chema - EVENT] f/\mu [Images\ chema - PATH] f/\mu,$$

where [*Complex images chemas*] are complex image schemes used in navigation.

Manifestation: rapid «reading» of navigational charts and data, manifested when using detailed navigational charts and visual data to accurately locate a vessel to avoid navigational obstacles.

Criterion: intuitive understanding of complex information.

Factor: $Images\ chemas_{int}$ – intuitive perception of images.

13. Time cycles and rhythms.

Formal description:

$$[TimeCycle] f/\mu [Rhythms] f/\mu,$$

where [*TimeCycle*] are time cycles related to navigation needs.

Manifestation: the subconscious coordination of shift work cycles, which affects the coherence of the shift service, violates safety monitoring [20].

Criterion: synchronization of work with the cycles of the day.

Factor: $Rhythms_{int}$ – intuitive matching of rhythms.

14. Impact of experience of events.

Formal description (11):

$$Echo - Event(Ev) \uparrow Echo - \\ - Events(Ev \uparrow) Multiple - Echo(f/\mu), \quad (11)$$

where Echo-Event(s) are echoes of past events in current solutions.

Manifestation: unconscious use of past experience, characterized by selective analysis of past events to improve future navigation strategies [21].

Criterion: «feeling» of historical patterns.

Factor: $Echo_{int}$ – an intuitive «echo» of events.

15. Features of the navigation zone.

Formal description (12):

$$\forall p Gs(\varepsilon | Ev(p\varepsilon) LAoT(f/\mu)) \cup p\varepsilon Ag Ag, \quad (12)$$

where Gs is the global system, εAg are local features or agents.

Manifestation: an intuitive understanding of the features of the navigation area, namely the failure to take into account the small attributes of the navigation area, including coastal currents, depths, and other local conditions affecting safety [22].

Criterion: deep, unconscious perception of the area.

Factor: $LAoT_{int}$, Ag_{int} – intuitive sense of place.

It becomes clear that intuitive manifestations in critical situations arise under the condition of insufficient qualifications of shipmasters in relation to navigational situations, they do not have enough experience and established algorithms of actions.

In view of this, the application of the model will make it possible to determine the intuitive behavior of operators-shipmasters in real time but, in order to devise an effective management strategy and prevent navigational risks, it is necessary to construct a method for the automated recovery of qualification parameters.

5. 2. Construction and formalization of the method for restoring qualification parameters of a shipmaster

In accordance with the above model of identification of intuitive actions of operator-shipmasters, it is envisaged to devise a method for the automated recovery of elements of shipmaster qualification parameters. The method contains 16 stages, each of which has an organizational and logical-formal description presented below.

Stage 1. The module performs a keyword search in the Lms Moodle database, indicators of the intellectual activity of the shipmaster during his/her training, relative to the full range of navigation parameters and points of the ship's route. The results of passing tests, assignments, video viewing facts, etc. are analyzed.

Information resources: LMS database Moodle (Modular Object-Oriented Dynamic Learning Environment).

Courses (mdl_course): contains information about each course created in the system, including course title, short description, start and end dates.

Course Modules (mdl_course_modules): contains information about the various modules or resources within each course, such as tests, assignments, videos, and forums.

Assignments (mdl_assign): information about assignments created within the course.

Tests (mdl_quiz): contains information about quizzes in the course, including questions and quiz settings.

Test Question (mdl_question): information about questions related to tests.

Quiz Results (mdl_quiz_attempts): contains data about the user's attempts to pass the quiz, including the date and time of the attempt, the number of points scored, and so on.

The result regarding the sufficiency of qualification parameters (QP) to each point of the route is fixed in advance.

Stage 2. The list of insufficient elements of each of the shipmaster's QPs participating in the route point to ensure navigation safety is determined. It is also necessary to take into account the rank of each checkpoint, given the location, the ranks of the same parameters at different points of the route may be different.

2. 1. Data collection and analysis of QP: data collection on insufficient qualification parameters of shipmasters. Analysis of existing data to identify potentially missing or weak QPs.

2. 2. Correlation analysis to determine the relationship between QP (Pearson correlation) (13):

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}, \quad (13)$$

where r is the Pearson correlation coefficient, x_i is the value of the i-th element of the variable, $\bar{x}$ is the average value of all elements of the variable x, y_i is the value of the i-th element of the variable y, $\bar{y}$ is the average value of all elements of the variable y.

It is used to identify the relationships between different QPs to understand which QPs affect the safety of sailing and which ones need improvement.

2. 3. Machine learning for QP clustering.

The k-means method for grouping QPs (14):

$$S_i^{(t)} = \left\{ x_p : \left\| x_p - \mu_i^{(t)} \right\| \le \left\| x_p - \mu_j^{(t)} \right\| \forall j, 1 \le j \le k \right\}, \quad (14)$$

where $S_i^{(t)}$ is the i-th cluster at the t-th iteration, x_p is the p-th data object to be classified into a cluster, $\mu_i^{(t)}$ is the centroid of the i-th cluster at the t-th iteration, $\left\| x_p - \mu_i^{(t)} \right\|$ is the distance from the p-th data object to the centroid of the i-th cluster, $\left\| x_p - \mu_j^{(t)} \right\|$ is the distance from the p-th data object to the centroid of the j-th cluster, k is the total number of clusters.

It is used to identify groups of QPs (as neighborhoods of a route point) that may have similar missing elements, and to detect absences within these groups.

2. 4. Graph theory for ranking QP.

The adjacency matrix for connections between QPs (15), (16):

$$A_{ij} = \begin{cases} 1 \text{ if } QP_i \text{ depends on } QP_j, \\ 0 \text{ otherwise,} \end{cases} \tag{15}$$

where 1 – there is a connection (dependence) between nodes i and j;

$$\deg(v) = \sum_{u \in G} A_{uv}, \tag{16}$$

where deg(v) is the node degree, $\sum_{u \in G} A_{uv}$ is calculated for all nodes u belonging to the graph G.

Used to determine the importance of each QP in the context of overall boating safety, especially in specific locations.

2. 5. Dynamic modeling to optimize training.

Bellman's recursive formula for the development of optimal strategies for recovery of QP (17):

$$V(i,j) = \max_{a \in A} \left\{ R(i,a) + \gamma \sum_{j \in S} P_{ij}(a) V(j) \right\}, \tag{17}$$

where $V(i,j)$ is a value function that determines the optimal value for state i and action j, A is a set of possible actions; $R(i, a)$ is the reward function that determines the reward for performing action a in state i, $Pij(a)$ is the probability of transition from state i to state j after performing action a, $V(j)$ is the value of state j, which was already determined, S is the set of possible states.

It is used to develop training or training plans that take into account individual insufficient QPs and their ranks in different locations.

Stage 3. Next, according to the list of insufficient elements of QPs, the difficulty of restoring each element is determined relative to the level of security at the future route point. It is determined how complex the QP element is in its structure and dependent on other QPs, what connections it has with them.

3. 1. Combinatorial analysis for structural complexity of QP.

Purpose: to estimate the possible number of states or configurations that each QP can take, taking into account the individual characteristics of the shipmaster.

The combinatorial number for calculating variations in QPs (18):

$$C(n,k) = \frac{n!}{k!(n-k)!}, \tag{18}$$

where $C(n, k)$ is the number of combinations k of elements with n.

Application: Determining the number of different ways a QP can be restored or improved based on its current state.

3. 2. Topological analysis to determine the dependence between QPs.

Purpose: to establish the structure of dependence between QPs and to identify key QPs.

Method: use of topological graphs and node centrality.

The formula of centrality of nodes (19):

$$C(v) = \frac{\sum_{s \neq v \neq t \in V} \sigma_{st}(v)}{\sigma_{st}}, \tag{19}$$

where $C(v)$ is the centrality of node v, σ_{st} is the total number of shortest paths from node s to t; σ_{st} (v) is the number of these paths passing through v.

Application: identification of QPs that have the greatest impact on overall safety.

3. 3. System dynamics to assess the impact of QP on safety.

Problem: modeling the dynamics of development of navigation skills in accordance with changes in other QPs.

Application of system dynamics: use of differential equations to describe the dynamics of changes in the QP.

Suppose navigation skills (N) depend on time (t) and the influence of other QPs (P).

Dynamics model (20):

$$\frac{dN}{dt} = f(N,P,t). \tag{20}$$

If the influence of other QPs increases over time, for example through additional training, this can have a positive effect on the development of navigation skills.

Stage 4. The shipmaster's individual tendency to perceive types of information is determined (also the speed of reaction to certain types of information signals (negative)) – for example, video information, the spectrum of the color palette is selected, for audio – the sound volume level, the accent of the English language, etc. Because for each shipmaster, the most digestible can be a specific set of information in a certain proportional structure.

4. 1. Linear regression for predicting reactions (21):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon, \tag{21}$$

where Y is the dependent variable that we are trying to predict, β_0 is the intercept coefficient, it represents the value of Y when all independent variables are equal to 0, $\beta_1, \beta_2, \ldots, \beta_n$ are coefficients for independent variables that show the average change in the dependent variable Y with unit variable X_i, X_1, $X_2, \ldots, X_n$ are independent variables used to predict Y, ε is an error term that represents the random deviation of Y from the regression line.

This formula is used to predict how a shipmaster will react to different types of information. Each coefficient β represents the weight that each type of information (e.g., visual or auditory) has in determining the overall response.

4. 2. Analysis of the principal components PCA (Principal Component Analysis) (22):

$$PCA(X) = W^{\mathrm{T}} X, \tag{22}$$

where $PCA(X)$ is the result of applying the method of principal components to the data set, W^T is the transposed matrix W (W is the matrix of weighting coefficients, where each column is a vector of one of the principal components, X is the original data set.

PCA is used to reduce the dimensionality of a dataset while preserving the most important information. In the context of this study, it will make it possible to determine which combinations of information signals are the most important for the operator-shipmaster.4. 3. Shannon entropy for evaluating information value (23):

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log p(x_i), \tag{23}$$

where $H(X)$ is the entropy of the data set, n is the number of possible states or events, $p(x_i)$ is the probability of the i-th event or state x_i in the data set, $\log p(x_i)$ is the logarithm of the probability of the i-th event.

Shannon entropy measures the amount of information in a data set. It becomes possible to assess which types of information are the most «informative» or «unpredictable» for the shipmaster, which can help in the optimization of information channels.

4. 4. Markov chains for predicting behavior (24):

$$P(X_{n+1}=x \mid X_n=x_n, X_{n-1}=x_{n-1},\ldots,X_0=x_0)= \\ =P(X_{n+1}=x \mid X_n=x_n), \quad (24)$$

where P is the probability, X_{n+1} is the next state of the system, x is the specific value of the next state of the system for which the probability is calculated, $X_n=x_n$ is the current state of the system, $X_{n-1}=x_{n-1}$, ..., $X_0=x_0$ are previous states systems from the latest to the starting state.

Markov chains can be used to model how an operator-shipmaster transitions from one reaction state to another according to the received information [23]. This makes it possible to assess how the shipmaster will react to a sequence of informational factors.

Stage 5. Metadata of the content of QP elements (in accordance with PDMLV) are formed, which require recovery taking into account the indicators of time to the route point according to the route planning tables. The generation of the time classification of QP on the route, the peculiarities of its change taking into account the individual characteristics of the operator [24] is performed. The logical structure of the formation of the qualification parameter in the cognitive model is determined.

5. 1. Ontological modeling for the classification of QPs (25):

$$\forall x\left(\mathrm{QP}(x)\rightarrow\exists y\left(\mathrm{Time}(y)\wedge\mathrm{Dependence}(x,y)\right)\right). \quad (25)$$

This formula is used to model the relationship between the QP and the terminal characteristics of the route. It is determined that for each QP there is a corresponding time parameter on which it depends [25]. This will allow one to organize the metadata of the checkpoint taking into account the time to the waypoint.

5. 2. Analysis of time series for forecasting changes in QPs (26) [26]:

$$\left(1-\pm\sum_{i=1}^{p}\phi_i L^i\left(1-L\right)^d Y_t=\left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t\right), \quad (26)$$

where Y_t is the time series value at time t, p is the order of the autoregression component of the model, ϕ_i is the autoregression coefficient, L is the time series shift operator (Lag operator), q is the order of the component of the moving average model, θ_i is the coefficient of the moving average, ε_t is the term of errors (or innovations) at time t.

The ARIMA (Autoregressive Integrated Moving Average) model allows one to analyze time series of QP to identify trends and predict future changes. It allows you to predict how time constraints to a waypoint affect the need to restore certain checkpoints.

5. 3. Cognitive modeling (27):

$$S_i=f\left(\sum_{j=1}^{n}w_{ij}X_j\right), \quad (27)$$

where S_i is the output signal or reaction of the i-th element of the system; $f(\cdot)$ is an activation function that can transform an input signal into an output state; $\sum_{j=1}^{n}$ – sigma notation, which indicates the summation of the contribution of all input signals; w_{ij} is a weighting factor that determines the influence of the j-th input signal on the i-th element; X_j is the input signal or state of the j-th element.

A cognitive network with weighting coefficients can be used to model the interaction between different QPs and determine their impact on the overall ability of the operator to effectively perform his/her duties [27]. This allows one to adapt training programs, taking into account the individual characteristics of each operator.

5. 4. Optimization algorithms for route planning (28):

$$D(v)=\min\left(D(u)+l(u,v)\right), \quad (28)$$

$D(v)$ is the distance from the initial node to node v, $D(u)$ is the distance from the initial node to node u, $l(u,v)$ is the length of the edge between nodes u and v.

Dijkstra's algorithm can be used to optimize route planning, taking into account time constraints and the need to restore different checkpoints. This helps determine the most efficient route, taking into account all the factors that affect the operator's performance of tasks.

Stage 6. A set of metadata is determined for all qualification parameters involved in ensuring safety at the future waypoint.

Structures are generated that most capaciously combine insufficient elements of QP relative to the route point (RP). In the case of points that have repetitions of QP elements, the distribution of content for restoration is provided for in such a way as to most effectively restore QP for each of RPs.

6. 1. Hierarchical cluster analysis for combining QP.

Goal: generation of structures that combine insufficient elements of QP with respect to RP in the form of a metric space (29):

$$d(X,Y)=\sqrt{\sum_{i=1}^{n}\left(x_i-y_i\right)^2}, \quad (29)$$

where $d(X, Y)$ is the distance between clusters X and Y, x_i, y_i are cluster elements.

This formula is used to determine the «distance» between different QPs. Clusters with the smallest distance are combined, creating groups of QPs that need to be restored at a certain route point.

6. 2. Bayesian network for content distribution optimization.

Goal: optimization of QP restoration, taking into account a number of expected RP (30):

$$P(A \mid B)=\frac{P(B \mid A)P(A)}{P(B)}, \quad (30)$$

where $P(A \mid B)$ is the conditional probability of event A under condition B, $P(B \mid A)$ is the conditional probability of B under condition A, $P(A)$, $P(B)$ are the probabilities of events A and B, respectively.

This formula helps determine the probability that a particular QP needs to be restored, given information about the waypoint and other associated QPs.

6. 3. Minimization of the time required to restore the QP.

6. 3. 1. Objective function:

$$\min Z = \sum_{i=1}^{n} w_i t_i,$$

where w_i is the weighting factor for the i-th QP, which reflects its priority or importance, t_i is the time required to restore the i-th QP.

6. 3. 2. Resource limitations (31):

$$\sum_{i=1}^{n} r_{ij} x_{ij} \le R_j,\ \forall j \in J, \tag{31}$$

r_{ij} is the time of use of the j-th resource for the i-th QP, x_{ij} is a binary variable that indicates the use of the j-th resource for the i-th QP, R is the total number of available hours of the j-th resource.

6. 3. 3. Time constraints and dependences (32):

$$t_i \ge t_{i-1} + d_{i-1},\ \ \forall i \in \{2,\ldots,n\}, \tag{32}$$

where d_{i-1} is the duration of the task immediately preceding the i-th QP.

6. 3. 4. Unclear elements.

To account for uncertainty, probability distributions or fuzzy variables can be used. For example, if t_i has a normal distribution (33):

$$t_i \sim N\left(\mu_i, \sigma_i^2\right), \tag{33}$$

where μ_i is the average recovery time for the i-th QP; σ_i^2 is the variance of recovery time.

6. 3. 5. Multiple optimization criterion.

If there are additional objectives, such as cost minimization, the Pareto-optimality approach (34) can be used:

$$\min Y = \sum_{i=1}^{n} c_i t_i, \tag{34}$$

where c_i is the cost of restoration of the i-th QP.

6. 3. 6. Binary variables:

$$x_{ij} \in \{0,1\},\ \ \forall i \in I,\ \forall j \in J,$$

where $x_{ij}=1$ if the j-th resource is used for the i-th QP, otherwise 0.

This approach is focused on minimizing the total time required to restore all necessary QPs to each of the waypoints, taking into account the repetition of elements and the need for their efficient distribution.

Stage 7. We generate relationships and, after them, start the process of combining metadata into an aggregate to optimize the perception of content by the master over time. At the same time, the resource of information perception, the physiological and motivational features of the shipmaster [28], the level of fatigue at the moment of time, and the current load on attention are taken into account.

7. 1. Graph theory for the analysis of relationships.

Purpose: determination of optimal relationships between QP metadata, taking into account various parameters.

Betweenness Centrality (35):

$$C_B(v) = \sum_{s \ne v \ne t} \frac{\sigma_{st}(v)}{\sigma_{st}}, \tag{35}$$

where $C_B(v)$ is the centrality of node v, σ_{st} is the total number of shortest paths from node s to t, $\sigma_{st}(v)$ is the number of these paths passing through v.

7. 2. Linear programming to optimize content perception.

Goal: minimization of the total time of content perception, taking into account physiological and cognitive limitations (36):

$$\min Z = \sum_{i=1}^{n} c_i x_i,\ \sum_{i=1}^{n} a_{ij} x_i \le b_j,\ \forall j, \tag{36}$$

where Z is the objective function, c_i is the cost of using the i-th resource, x_i is the amount of use of the i-th resource, a_{ij} is the coefficient that determines the impact of the i-th resource on the j-th constraint, b_j is the limit of the j-th constraint.

7. 3. Neural networks for modeling perceptual abilities.

An extension of the neural network formula: let x include not only the input but also parameters such as the state of fatigue (f), the level of attention (a), and the available attentional load (l). Then the extended formula of the neural network can be expressed as (37):

$$y = f\left(W \cdot \left(x \oplus f \oplus a \oplus l\right) + b\right), \tag{37}$$

where $\oplus$ means concatenation of vectors.

7. 4. Modeling fatigue and attention.

Differential equations (38) can be used to display the dynamics of fatigue and attention:

$$\frac{df}{dt} = -\alpha f + \beta,\ \frac{da}{dt} = -\gamma a + \delta, \tag{38}$$

where α, β, γ, δ are parameters that describe the rate of fatigue and attention reduction and their recovery, respectively.

7. 5. Integration of time series.

Time series can be integrated into the model to account for the history of information perception by the master. Using RNN (Recurrent Neural Network) or LSTM (Long Short-Term Memory) to process a sequence of input data (39):

$$h_t = \mathrm{LSTM}\left(x_t, h_{t-1}\right),\ y_t = \mathrm{softmax}\left(W_y h_t + b_y\right), \tag{39}$$

where h_t is the hidden state at time step t, x_t is the input data at time step t, W_y, b_y are the parameters to be trained.

7. 6. Activation functions.

Depending on the type of task, various activation functions can be used for different layers of the network, such as ReLU (Rectified Linear Unit) or sigmoid for classification tasks.

Stage 8. An automated search by metadata in the database of the company, associations of companies, databases of maritime states is launched. Where the base is the records of the navigation bridge on each ship of the company regarding the required number of cameras, the viewing angle of which is relative to each source of information, the workplace of the shipmaster according to the qualification parameter (element). Priority is given to data regarding a route point in the same location (in previously traveled routes), second priority regarding route points in other locations, but with a completely identical navigational situation (observance of all external and internal factors by more than 90 %). In other cases, the situation must correspond to at least 80 % of the main elements of QP and 70 % of the secondary ones, an example is CATZOC (Category Zone of Confidence). Databases are confidential.

8. 1. Fuzzy logic for prioritization.

Purpose: taking into account priorities and percentages of conformity of navigation situations (40):

$$Z = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}, \tag{40}$$

where Z is the output parameter of fuzzy logic, x_i is the input parameter (for example, the degree of correspondence to the situation), w_i are the weights corresponding to the priorities.

8. 2. Search optimization in databases.

The goal: to improve the efficiency and accuracy of data retrieval, taking into account complex matching criteria.

Using the binary search algorithm (41):

$$\text{while } l \le r: \ m = \left[\left(l+r\right)/2\right] \text{ if array}\left[m\right] < \text{target:}$$
$$l = m+1 \text{ else if array}\left[m\right], \tag{41}$$

where l and r are the left and right limits of the search in the array, m is the middle of the range, array[m] is the element at position m, target is the searched value:

$$\text{target: } l = m+1 \text{ else if array}\left[m\right] > \text{target:}$$
$$r = m-1 \text{ else: return } m,$$

where array[m] is the element at position.

8. 3. Data visualization for analysis.

The goal: to provide intuitive visualization for analyzing large data sets.

Using network graphs (42):

$$\text{draw}\left(V,E\right): \text{ for each } v \in V:$$
$$\text{drawVertex}\left(v\right) \text{ for each}\left(u,v\right) \in E: \text{drawEdge}\left(u,v\right), \tag{42}$$

V – network vertices (for example, qualification parameters), E – edges connecting vertices (showing relationships), drawVertex and drawEdge – functions for visualizing vertices and edges.

Step 9. The video information is analyzed in a video sequence for images every 5–30 seconds, depending on the level of risk at the given waypoint.

9. 1. Use of convolutional neural networks, CNN (Convolutional Neural Networks) for image analysis.

Goal: effective analysis and recognition of objects in video recordings (43):

$$f\left(X\right) = ReLU\left(W * X + B\right), \tag{43}$$

where X is the input image, W is the filter weights, B is the bias, $*$ is the convolution operation, ReLU is the activation function (for example, Rectified Linear Unit).

9. 2. Change detection algorithms for determining the level of risk.

Purpose: automatic detection of changes in video recordings that may indicate an increased level of risk (44):

$$D\left(X_t, X_{t-\Delta t}\right) = \left\| X_t - X_{t-\Delta t} \right\|, \tag{44}$$

where D is the measure of the difference between the current frame X_t and the previous $X_{t-\Delta}$, Δt is the time interval between frames.

9. 3. Time series analysis for risk assessment.

Purpose: Assessment of the level of risk taking into account the time characteristics of the video sequence (45):

$$R_t = \alpha \sum_{i=1}^{n} w_i R_{t-1} + \varepsilon_t, \tag{45}$$

where R_t is the risk assessment at time t, w_i are weighting factors reflecting the influence of previous data, ε_t is random noise, α is the smoothing factor.

Step 10. The intelligent module performs image recognition and determines the range of the video series, such that according to the data from the server regarding ECDIS, AIS (Automatic Identification System), GPS, ARPA (Automatic Radar Plotting Aid), on more than 80 % corresponds to the actual navigation situation.

10. 1. Deep learning for image recognition.

Purpose: automatic determination of characteristics of the navigation situation from video recordings (46):

$$f\left(X\right) = \text{softmax}\left(W \cdot g\left(X\right) + b\right), \tag{46}$$

where X is the input image, $g(X)$ is a feature function extracted from a deep neural network, W and b are weighting factors and biases, softmax is an activation function for classification.

10. 2. Machine learning to determine data relevance.

Purpose: analysis of video data for correspondence with information from ECDIS, AIS, GPS, ARPA. Algorithm of random forests for classification (47):

$$P\left(y \mid X\right) = \frac{1}{N} \sum_{i=1}^{N} I\left(h_i\left(X\right) = y\right), \tag{47}$$

where $P(y \mid X)$ is the probability that image X belongs to class y, N is the number of trees in the ensemble, $h_i(X)$ is the solution of the i-th tree, I is the indicator function.

10. 3. Compliance analysis using statistical methods.

Purpose: assessment of the percentage of correspondence between navigation data and images (48):

$$V = \frac{1}{m} \sum_{i=1}^{m} \left(similarity\left(D_i, S_i\right)\right), \tag{48}$$

where V is the average correspondence, m is the number of measurements, D_i is the data from the intelligent module, S_i is the standard navigation data (ECDIS, AIS, GPS, ARPA), similarity is the similarity detection function.

Stage 11. Video fragments selected according to the described criteria should contain only examples of actions to ensure security in relation to previously defined fuzzy rules.

11. 1. Deep learning model with transformers for video analysis.

Goal: use transformers to recognize key video features that meet security requirements.

Transformer encoder:

$$H = \text{LayerNorm}\left(X + \text{MultiHeadAttention}\left(X\right)\right),$$

$$Z = \text{LayerNorm}\left(\text{H+FFN}\left(\text{H}\right)\right),$$

where X is input data (video images), MultiHeadAttention is a multidimensional attention mechanism, FFN (Feedforward Neural Network) is a fully connected network, LayerNorm is layer normalization.

11. 2. The SVM (Support Vector Machine) method for video classification.

Objective: using SVM to accurately classify video fragments using defined criteria (49):

$$f(x)=\operatorname{sign}\left(\sum_{i=1}^{n}\alpha_i y_i K(x_i,x)+b\right), \quad (49)$$

where x_i are vectors of support vectors, y_i are class labels, K is a kernel function, α_i, b are parameters trained by the model.

11. 3. Semantic analysis of video content.

Purpose: Automated semantic analysis of video content to detect security compliance. Using analysis of deep semantic features (50):

$$S=\sum_{j=1}^{m}w_j\cdot \text{SemanticFeature}(X,j), \quad (50)$$

where S is the semantic evaluation of the video, w_i is the weight of the j-th semantic feature, SemanticFeature(X,j) is a function for determining the j-th semantic feature in video X.

Stage 12. Broadcasting of video clips using the means and methods of augmented reality, synchronously with the navigation watch. This involves the use of special glasses. In addition, the content delivery mode is determined in such a way as not to overload and/or distract the shipmaster from the current tasks while on watch. The use of augmented reality is an effective way of presenting information since it is not possible to install other software on on-board PCs.

12. 1. Multifactor model of assessment of visual comfort.

Purpose: evaluation of visual comfort and overload when using augmented reality (51):

$$V_C=\alpha\cdot E_C+\beta\cdot S_C+\gamma\cdot T_C, \quad (51)$$

where V_C is general visual comfort, E_C is ergonomic comfort (for example, the comfort of glasses), S_C is sensory comfort (impact on vision), T_C is temporal comfort (impact on attention), α, β, γ are weighting factors for each factor.

12. 2. Predictive coding model for content flow.

Goal: optimization of content flow based on the current situation and behavior of the shipmaster (52):

$$P_t=\sigma(W\cdot H_{t-1}+U\cdot X_t+b), \quad (52)$$

where P_t is the predicted flow of content at time t, H_{t-1} is the previous state of the model, X_t is input data (for example, signals from ECDIS, AIS), W, U, b are model parameters, σ is a sigmoid activation function.

12. 3. Adaptive load management algorithm.

Purpose: adaptation of the flow of content to the level of load and fatigue of the shipmaster (53):

$$L_t=f(C_t,V_t,M_t), \quad (53)$$

where L_t is the shipmaster's load level at time t, C_t is the current content, V_t is the fatigue assessment, M_t is the attention monitoring, and f is the adaptation function.

Stage 13. The concentration of information, which is presented with a different degree of intensity over time, determines the output parameter (10) and predicts the linguistic scale of the level of difficulty of perception as a dynamically changing coefficient. The complexity of perception can cause a critical reaction, in the case when there is an effect of accumulation and overload, excessively intense – extreme [29].

13. 1. Linguistic variable model for assessing the complexity of perception.

Purpose: assessment of the dynamic complexity of information perception (54):

$$S(t)=\sum_{i=1}^{n}\lambda_i\cdot f_i(t), \quad (54)$$

where $S(t)$ is the difficulty of perception at time t, λ_i is the linguistic coefficients for different types of information, $f_i(t)$ is the intensity of the i-th type of information in time.

13. 2. Model of assessment of psychological load.

Purpose: determination of the level of psychological stress and the risk of overload (55):

$$P(t)=\int_0^t e^{-\alpha(t-\tau)}\cdot I(\tau)d\tau, \quad (55)$$

where $P(t)$ is the psychological load at time t, $I(\tau)$ is the intensity of the information flow at time τ, α is the attenuation coefficient, which determines the speed of «forgetting» or adaptation.

13. 3. Model of dynamic adaptation of information flow.

Purpose: adaptation of information flow to prevent critical overload (56):

$$D(t)=\theta\cdot\left(1-e^{-\beta\cdot L(t)}\right), \quad (56)$$

where $D(t)$ is the degree of adaptation of the information flow over time, $L(t)$ is the current load level, β are model parameters that determine the speed and intensity of adaptation.

Stage 14. Based on this, it is important to develop a circuit with feedback, which will be able to form a control signal at the input of the system to dose the additional load for the restoration of the QP in real time.

14. 1. Feedback system with an adaptive controller.

Purpose: load regulation based on the current state of the system and external factors [30, 31] (57):

$$U(t)=K_p e(t)+K_i\int_0^t e(\tau)\mathrm{d}\tau+K_d\frac{de(t)}{dt}, \quad (57)$$

where $U(t)$ is the control signal in time, $e(t)$ is the error between the desired and actual state of the system, K_p, K_i, K_d are the coefficients of proportional, integral, and differential control.

14. 2. Model of fuzzy logic controller.

Purpose: formation of a control signal based on fuzzy logic to adapt to uncertainty and changing conditions (58):

$$U(t)^*=\sum_{i=1}^{n}w_i\cdot F_i(t), \quad (58)$$

where $U(t)^*$ is a control signal, w_i are weighting factors, $F(t)$ are fuzzy rules based on current conditions and parameters.

14. 3. Model of dynamic load adaptation.

Purpose: dynamic load adjustment based on the current state of the system and set parameters (59), in the form of a superposition:

$$L(t)=L_0+\sum_{i=1}^{n}\alpha_i\cdot X_i(t), \tag{59}$$

where $L(t)$ is the total load of the system, L_0 is the base load, α_i is the influence coefficient, $X_i(t)$ is the external factors or parameters of the system.

Stage 15. It is important to take into account that in certain situations, when the preliminary calculation of the restoration of the set of qualification parameters does not give sufficient confidence in ensuring safety, the captain needs to replace a member of the watch service or strengthen the watch.

15. 1. The determination of the human factor component is based on the analysis of the performance of operations and tasks during the navigation watch.

The initial stage of such identification begins during training practice using simulators. It is when working with simulators that it is possible to record significant lags in the execution time of commands, operations, failures in the logic of sequential actions, etc.

Purpose: to identify the individual characteristics of shipmasters, based on the data of training practices (60):

$$I=\sum_{i=1}^{n}\left(w_{ti}\cdot T_i+w_{pi}\cdot P_i+w\cdot C_i\right), \tag{60}$$

where I is an integrated indicator of individual efficiency, T_i are time indicators in training practices, P_i are psychological indicators, C_i are cognitive indicators, w_{ti}, w_{pi}, w_{ci} are weighting factors.

15. 2. Advanced model of artificial intelligence for risk prediction.

Purpose: to assess the risk associated with insufficient qualification parameters using deep learning.

Using a modified neural network with LSTM architecture for time series analysis (61), (62):

$$R_t=\sigma\left(W_f\cdot\left[H_{t-1},X_t\right]+b_f\right),\ I_t=\sigma\left(W_i\cdot\left[H_{t-1},X_t\right]+b_i\right),$$
$$O_t=\sigma\left(W_0\cdot\left[H_{t-1},X_t\right]+b_o\right), \tag{61}$$

$$C_t=f_t\cdot C_{t-1}+i_t\cdot\tanh\left(W_C\cdot\left[H_{t-1},X_t\right]+b_C\right),$$
$$H_t=o_t\cdot\tanh\left(C_t\right), \tag{62}$$

where R_t is the risk at time t, H_{t-1} is the previous state of the network, X_t is the input data, W_f, W_i, W_o, W_C and b_f, b_i, b_o, b_C are the network parameters, σ is the sigmoid activation function, f_t, i_t, o_t – lost qualifying elements, input and output LSTM elements.

15. 3. Resource allocation optimization model.

Purpose: Allocation of resources and guidelines based on current needs and qualifications (63):

$$O=\min\left(\sum_{j=1}^{m}r_j\cdot\left(\sum_{i=1}^{n}\lambda_{ij}\cdot Q_i\right)\right), \tag{63}$$

where O is the optimized solution, r_j are the resources available for the j-th task, λ_{ij} are the weighting factors for resource allocation, Q_i are the qualification parameters of the i-th shipmaster.

Stage 16. In the course of dynamically changing navigation data, a situation may arise in which there is a high probability of occurrence of trigger clusters of QP elements. In such cases, the intelligent system can take control of the ship, synchronously informing the captain and watch crew about such a decision.

At the same time, management is not performed over the entire ship but only by the workplace of the watch crew member.

16. 1. Advanced anomaly detection model using artificial intelligence.

Using a neural network to detect anomalies [32] (64):

$$A(x)=\mathrm{softmax}\left(W_2\cdot\mathrm{ReLU}\left(W_1\cdot x+b_1\right)+b_2\right), \tag{64}$$

where W_1, W_2, b_1, b_2 are network parameters, x is a vector of input data (for example, navigation parameters and ship state), ReLU is an activation function, softmax is a function for output classification.

16. 2. Complex model of optimization of interaction between man and machine.

Using a weight model to optimize interaction (65):

$$O(t)=\sum_{i=1}^{n}\left(\alpha_i\cdot H_i(t)+\beta_i\cdot S_i(t)\right), \tag{65}$$

where $O(t)$ is the optimized solution at time t, $H_i(t)$, $S_i(t)$ are indicators of human and system interaction, respectively, α_i, β_i are coefficients that take into account the importance of each aspect of interaction.

5. 3. Construction of a data processing scheme to enable the method of restoration of qualification parameters of a shipmaster

Therefore, a comprehensive approach is proposed, starting with the data collection and analysis group. A scheme has been devised that reveals the sequence of actions aimed at effective assimilation of information (Fig. 5–8).

The process of data analysis consists of several stages, starting with the analysis of indicators of intellectual activity, which includes the evaluation of test results and course information in the LMS Moodle system.

At the next stages, insufficient elements of cognitive potential (QP) are determined, individual propensity to perceive information is analyzed, and metadata is formed for better understanding and optimization of cognitive processes. The output of each stage is used to improve subsequent stages, ensuring deep communication and integration between processes.

Next, starting with the assessment of the difficulty of restoring QP, the data on insufficient QP from the previous stage are analyzed to determine their complexity. At the next stage, QP metadata is formed and analyzed to prepare information for automated search and selection of video documents. The results of these analyzes are used to optimize the perception of content and intelligent analysis of images, which, in turn, contributes to increasing the safety of navigation.

The next component is optimization of content perception based on predictions of reactions and assessment of QP complexity, automated search by metadata to select relevant data, and analysis of video recordings to determine effective approaches to learning and recovery. The results of these analyzes serve as the basis for intelligent analysis of images and further concentration of information, which allows for the development of effective strategies for improving cognitive functions.

In turn, the process of optimizing content perception and restoring cognitive potential unfolds through several interrelated stages. Starting with an intelligent analysis of images that uses data on the complexity of the QP and video recordings, video fragments are then selected for further broadcasting through augmented reality.

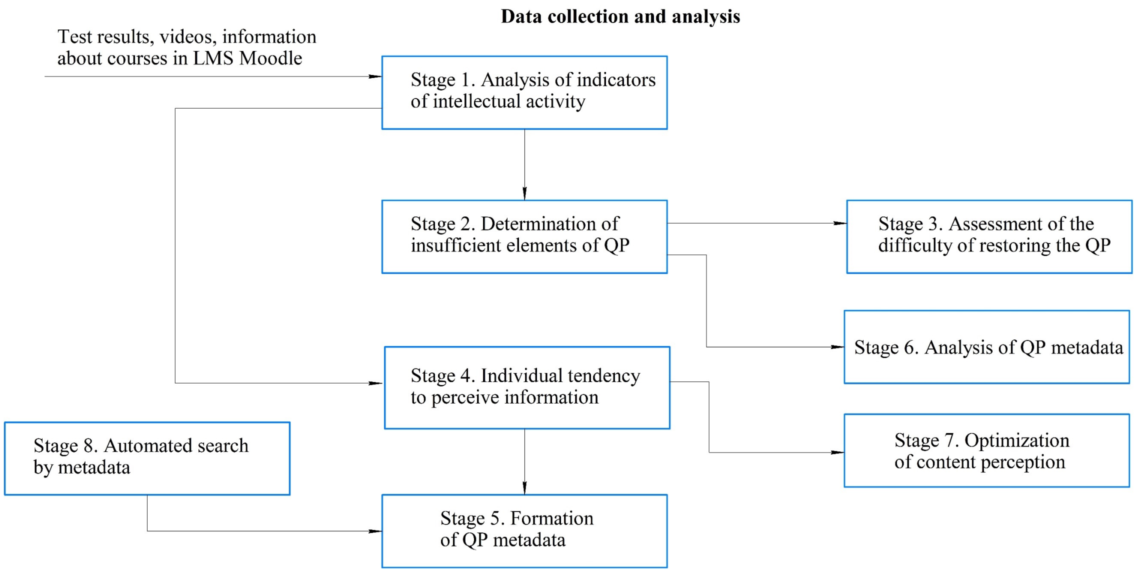

Fig. 5. Operationalization of the data collection and analysis group

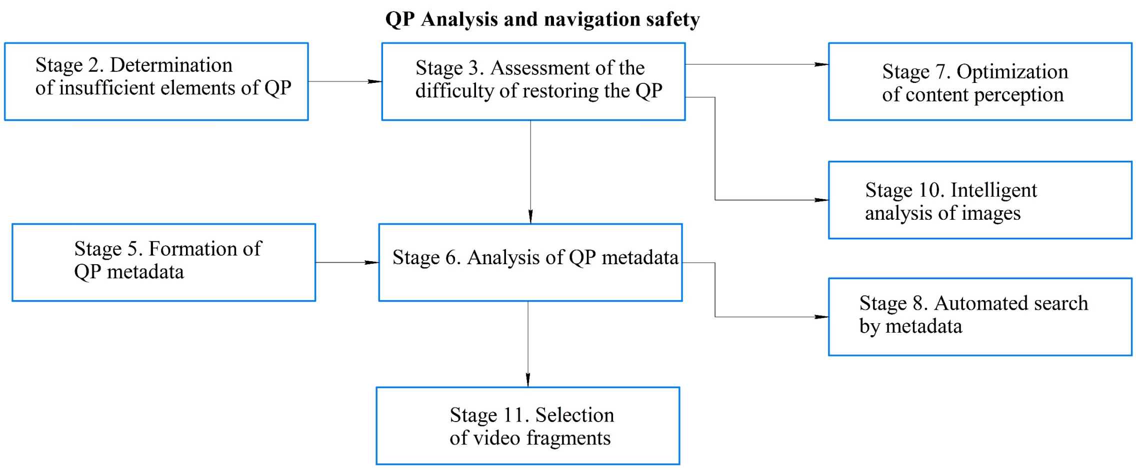

Fig. 6. Operationalization of the navigation safety and analysis group

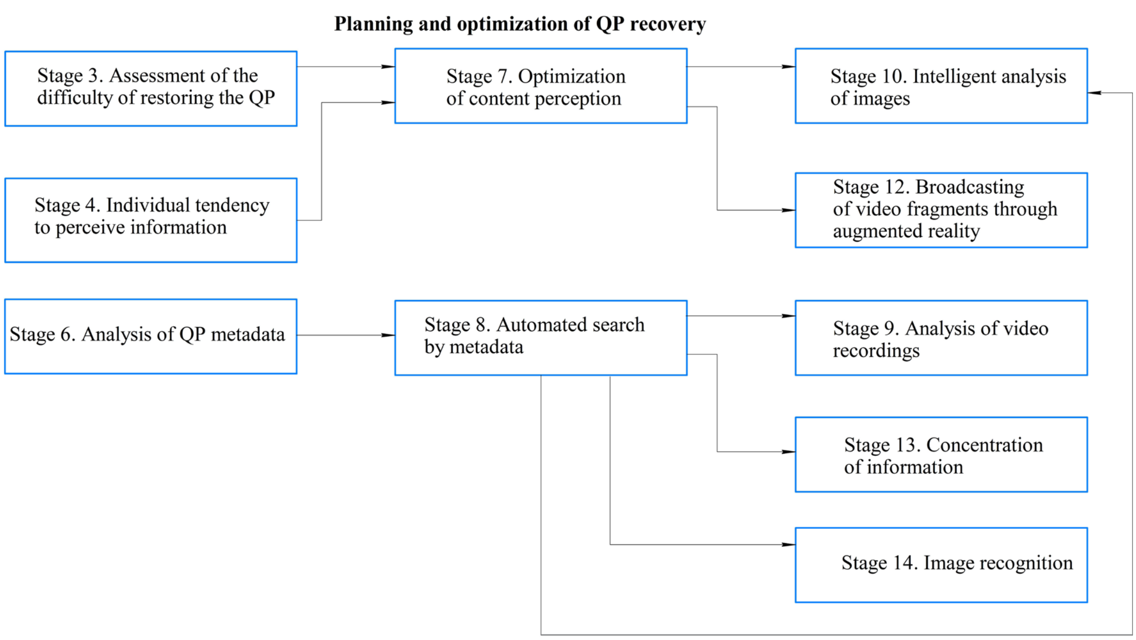

Fig. 7. Operationalization of the group of planning and optimization of restoration of qualification parameters

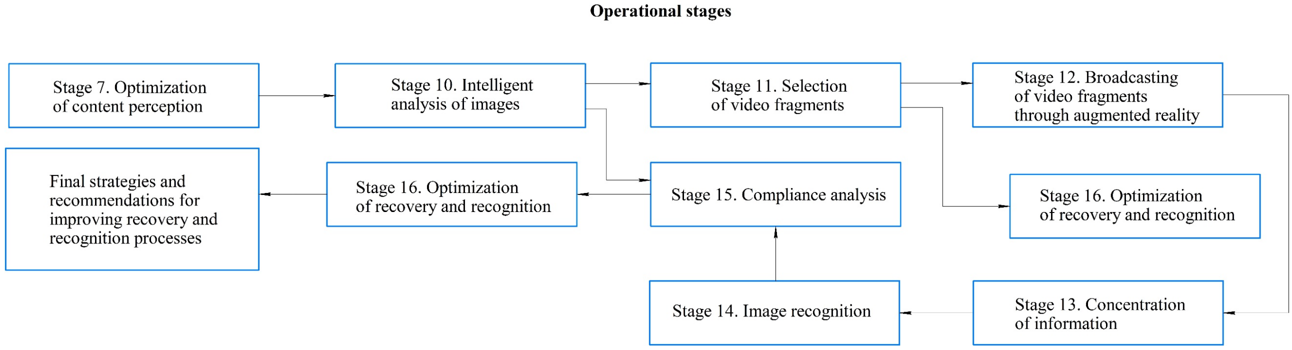

Fig. 8. Operationalization of a group of operational stages of the model

The concentration of information leads to the recognition of images and the analysis of their correspondence to navigation data. The final stage includes optimization of recovery and recognition based on all analyzed data, which leads to the formation of final strategies and recommendations to improve these processes.

In order to determine the effectiveness of the proposed approach, in real time, at the beginning of December 2023, an experiment was conducted on the passage of a ship on the Rotterdam-Amsterdam route. The initial and final waypoints of the routes were defined as the most difficult (Fig. 9).

The experiment was carried out taking into account the watchkeeping by its members:

1. Captain/watch member from 08:00 to 12:00.
2. Captain/watch member from 20:00 to 24:00 (experience as a captain – 6 years, total experience at sea – 19 years).
3. First mate/watch member from 04:00 to 08:00, conducting the navigation watch.
4. First mate/member of the watch from 16:00 to 20:00 (experience as first mate – 8 years, total experience at sea – 16 years).
5. Second assistant captain/watch member from 24:00 to 04:00 and from 12:00 to 16:00 (experience as a second assistant – 3 years, total experience at sea – 10 years).

Taking into account the complexity of the navigation area and the approximate time of approach to the starting point of the mooring operation, which was 42 minutes, the knowledge recovery system was launched in synchronous mode. The time of 27 minutes proved to be sufficient for the automated selection and representation of close data in the form of photos and video fragments to the shipmaster under close navigational circumstances. It took 3 minutes 38 seconds to analyze and create content to restore qualification parameters.

In this way, it was possible to significantly increase the confidence of the shipmaster in his actions, the analysis of which had no signs of intuition, and therefore the operation of approaching the port and mooring in a new location was performed at a sufficient level of safety. No deviations from the planned course and speed were detected.

5. 4. Modeling the dynamics of change in the level of danger, taking into account the time of restoration of the qualification parameters of a shipmaster

In order to model the effectiveness of restoration of qualification parameters, we introduce the function $f(x)$. This will allow reflecting the impact of information from navigation devices on the decision-making process. At the same time, x can be a variable describing the current state of the vessel management system (66):

$$f(x) = k_1 x_1 + k_2 x_2 + \ldots + k_7 x_7, \tag{66}$$

where x_1 – ECDIS output (vessel course), x_2 – radar output, ... x_7 – gyrocompass output.

Coefficients k_1, k_2, ...k_7 represent the weight of information from the device in the decision-making process. These coefficients can be determined based on the level of complexity of processing information from each device.

Now, $g(t)$ will be the function representing the external influence on the system.

Based on the time levels of decision-making, $g(t)$ can be divided into several intensity levels:

– very low: $g(t)=A$ (small constant value);
– low: $g(t)=B$ (slightly more than A) and so on until (x_7);
– critical: $g(t)=F$ (the largest value).

Fig. 9. Rotterdam-Amsterdam route processing

By substituting all this into the differential equation:

$$b_1\frac{dx}{dt}+b_0x=g(t),$$

the output of the system x depending on the external conditions $g(t)$ was obtained, and on the basis of this output, the behavior of the variable y in the equation:

$$a_1\frac{dy}{dt}+a_0y=f(x)$$

was modeled.

To proceed with the solution, specific values of coefficients obtained from experimental data were used.

Then:

– a_0 – reflects the direct time required for initial perception and understanding of the navigation situation;

– a_1 – reflects the delay associated with the time to make a decision after perceiving the navigational situation. This includes analyzing information, discussing with team members, etc.;

– b_0 – the time required to interact with specific equipment on board. Also includes physical actions such as turning on the radar, setting parameters, etc.;

– b_1 – the time required to relate the current navigational situation to previously learned or known information, which includes recalling past situations, familiarization with maps or other comparative analyses.

For mathematical modeling, two options (short-term and long-term) were adopted:

– a_0 – time to perceive the situation: 2 minutes (27 minutes);

– a_2 – decision-making time: 3 minutes (30 minutes);

– b_0 – time to restore knowledge by interacting with the equipment: 3 minutes (27 minutes);

– b_1 – time for assigning restored knowledge: 1 minute (3 minutes).

For equation (67):

$$\frac{d^2y}{dt^2}+a_1\frac{dy}{dt}+a_0y=b_1\frac{dx}{dt}+b_0x, \tag{67}$$

after introducing new coefficients into the differential equation and using the Laplace transform, the following was obtained:

Converted coefficients: a_1s+a_0, b_1s+b_0.

Taking into account the initial conditions $y(0)=2$ and $\frac{dy}{dt}(0)=0$, as well as the level of risk – $x(t)$, in the form of a step function that changes from 2 to 5 at $t=4$ min, after performing the Laplace transformation and solving the equation, the inverse Laplace transformation follows [33], to obtain $y(t)$ in the time domain.

It was assumed that at the beginning $y(t)$ is equal to 2. At $t=4$, a sharp change begins due to a sudden storm wind, and the system begins to respond to this change. Based on this, we define $x(t)$ as a step function: $x(t)=2+3u(t-4)$, where $u(t)$ is a unit jump function and its derivative: $dx/dt=3\delta(t-4)$ and $\delta(t)$ is a Dirac delta-function [34].

The Laplace transform (68) was used:

$$s^2Y(s)+3sY(s)+2Y(s)=sX(s)+3X'(s). \tag{68}$$

Based on the function $x(t)$, its Laplace transform:

$$X(s)=\frac{2}{s}+\frac{3e^{-4s}}{s},\quad X'(s)=-3e^{-4s}.$$

Next, $x(t)$ was found and we perform the inverse Laplace transform.

Therefore, the differential equation (69) was obtained:

$$\frac{d^2y}{dt^2}+3\frac{dy}{dt}+2y=3\delta(t-4)+\frac{5}{t},$$

$$x(t)=2+3u(t-4),\ \frac{dx}{dt}=3\delta(t-4). \tag{69}$$

The rewritten equation in the Laplace domain (70):

$$s^2Y(s)+3sY(s)+2Y(s)=3e^{-4s}+\frac{5}{s}. \tag{70}$$

To determine the coefficients A, B, and C, partial fractionation was performed. The fraction is decomposed into simple components (71):

$$\frac{1}{s(s+1)(s+2)}=\frac{A}{s}+\frac{B}{s+1}+\frac{C}{s+2}. \tag{71}$$

Using these equations, the coefficients were found:

– for s^2: $A+B+C=0$;

– for s^1: $3A+2B+C=0$;

– for s^0: $2A=1$, $A=1/2$.

Substituting the value of A into the first and second equations allowed us to obtain:

$$B+C=-\frac{1}{2}\text{ and }2B+C=-\frac{3}{2},$$

then:

$$A=\frac{1}{2},\ B=0,\ C=-\frac{1}{2}.$$

From previous analysis:

$$Y(s)=\frac{1/2}{s}+\frac{0}{s+1}+\frac{-1/2}{s+2}.$$

The inverse Laplace transform is applied to each of these components:

– for $\frac{1/2}{s}:\lambda^{-1}\left\{\frac{1/2}{s}\right\}=\frac{1}{2}$;

– for $\frac{0}{s+1}:\lambda^{-1}\left\{\frac{0}{s+1}\right\}=0$;

– for $\frac{-1/2}{s+2}:\lambda^{-1}\left\{\frac{-1/2}{s+2}\right\}=-\frac{1}{2}e^{-2t}$.

Thus, $y(t)=\frac{1}{2}-\frac{1}{2}e^{-2t}$, taking into account the initial conditions and coefficients.

Therefore, the obtained dependences with the function of restoring the qualification parameters of a shipmaster will match the following plots (Fig. 10, *a, b*).

In turn, if we model the delay in the restored qualification parameters with input data $a_0=3$, $a_1=2$, $b_0=15$ and $b_1=12$, dependences were determined (Fig. 10, *c, d*).

The resulting function $y(t)$ describes the change in the level of danger to navigation as a function of time in response to a sudden change in weather conditions.

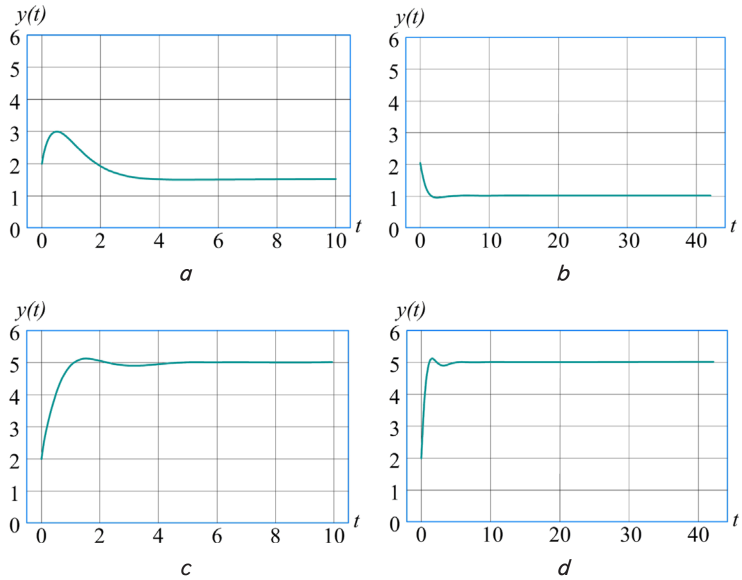

Fig. 10. Dependence plots of the level of risks over time:
a – the level of danger during a short-term operation with the function of restoring qualification parameters; *b* – the level of danger during a long-term operation with the function of restoring qualification parameters; *c* – the level of danger during a short-term operation without the function of restoring qualification parameters; *d* – the level of danger during a long-term operation without the function of restoring qualification parameters

This feature can be used to manage shipping safety in the following ways:

1. Hazard level prediction: using $y(t)$, it is possible to predict the hazard level at certain time intervals. This will help the captain and the team to be ready for future conditions.
2. Maneuvering decision: when the level of danger reaches or approaches a critical point, a decision can be made to change course, reduce speed, or seek cover.
3. Crew QP recovery: using this feature, training scenarios can be created for the crew to better understand and respond to changing conditions.
4. Creation of automatic warning systems: the function can be built into automatic warning systems on board, which will signal the crew about the increasing level of danger, giving them more time to react.

Overall, the resulting function $y(t)$ provides a tool for understanding and managing the risks associated with shipping in difficult weather conditions. However, it should be taken into account that mathematical modeling must be performed for each individual shipmaster separately.

6. Discussion of results of investigating the application of the devised safety control system in ship management

Our results of the research are explained by the fact that a model of identification of intuitive actions and a method of restoring the qualification parameters of operator-shipmasters were constructed in combination.

Thus, 15 relevant categories were determined using the model of identification of intuitive actions of operator-shipmasters (chapter 5. 1). Each of the categories made it possible to identify variables that indicate intuitive behavior:

– Z_{α} ?$_{int}$ – quick perception of the situation;
– τ/T_{int} – a choice that is not provided by the instruction;
– $Cog_{int}(a,b)$ – understanding the sequence of actions in complex operations;
– Ξ_{int} – adaptation to an unknown data set;
– $LAoT_{int}$ – synchronous actions with tools and equipment;
– Ev_{int} – response to events;
– $Rewards_{int}$, $Effects_{int}$ – perception of rewards and consequences;
– $Idea_{int}$ – generation of ideas;
– $Resource{-}Search_{int}$, $Time{-}Synthesis_{int}$ – resource search and time synthesis;
– $WorldEv_{int}$ – perception of world events;
– $Time_{int}$ – time display;
– $Images\ chemas_{int}$ – perception of images;
– $Rhythms_{int}$ – coordination of rhythms;
– $Echo_{int}$ – «echo» of events;
– $LAoT_{int}$, Ag_{int} – sense of place.

All these variables are identified by only two parameters, the time of manifestation compared to the time of performing similar tasks under the conditions of previous training or existing work experience. During the analysis, when the speed of manifestation is more than two times, in difficult situations, the action was considered intuitive, in 56 % of cases it led to the application of the method of restoring the qualification parameters of operators-shipmasters. It is possible not to perceive such circumstances only in cases where experienced captains participate in the experiment, as discussed in study [35].

The peculiarity of the proposed method and our results is the application of 16 consecutive formal-analytical stages, each of which has a purpose, an organizational structure of data processing, and a mathematical description.

The analytical part of each stage of the method was developed taking into account the individual characteristics of operator-shipmasters, their reactions, prognostic models, correlation, and regression (stage 4), which is widely used in the research of scientists who study the danger factors of ship navigation [36]. Among the investigated indicators.

Taking into account large data sets, in real time, neural networks, in particular LSTM, are applied (step 7), which perform well in tangential tasks during the analysis and detection of fatigue of navigators in study [37].

However, compared to studies [38], this set of stages also included the analysis of video information (stage 9), by means of convolutional neural networks (CNN) and time series, which has high indicators of the ability to identify target vessels that may pose a danger.

In general, all stages of the method were united by known formal approaches and methods, which can be classified according to the following directions:

– statistical analysis (stage 2. 2. Pearson correlation (r); stage 9. 3. Time series analysis (R_t); stage 10. 3. Statistical methods (V));

– clustering and classification (stage 2. 3. QP clustering stage $\left(S_i^{(t)}\right)$; 9. 1. convolutional neural networks ($f(X)$); stage 10. 2. Machine learning ($P(y|X)$); stage 11. 2. SVM for video classification ($f(x)$));

– optimization and solutions (stage 5. 4. Optimization algorithms ($D(v)$); stage 6. 3. Minimization of QP recovery time; stage 7. 2. Linear programming (Z); stage 15. 3. Optimization of resource allocation (O));

– modeling and forecasting (stage 3. 3. System dynamics (dN/dt); stage 7. 3. Neural networks (y); stage 7. 5. Integration of time series (RNN, LSTM); stage 10. 1. Deep learning ($f(X)$); stage 12. 2. Predictive coding model (P_t);

– dynamic systems and control (stage 7. 4. Modeling fatigue and attention (differential equations); stage 14. 1. Feedback system ($U(t)$); stage 14. 2. Fuzzy logic controller model ($U(t)^*$);

– integration and synthesis (stage 8. 4. data visualization; stage 11. 1. Transformers for video analysis (H, Z); stage 12. 3. Adaptive load management algorithm (L_t); stage 13. 1–13. 11. Integrated indicators and solutions (S_t, P_t, O_t, U_s)).

Given the proposed integration, the success is in the use of the proposed method, which allows timely identification and correction of qualification deficiencies, the importance of which affects the safety of shipping, as indicated in study [39].

However, there are certain objective limitations inherent in this study that depend on the conditions of application of the proposed solutions. Currently, it is impossible to ensure the full integration of the proposed algorithmic solutions due to the ban by international maritime organizations and companies. For this reason, it is necessary to duplicate navigation data on an autonomous computer that is not connected directly to navigation information systems. This causes a certain time delay, up to 1 minute depending on the complexity of the situation, but given the high inertia of the vessel, in the vast majority of cases (more than 90 %) it does not affect navigational safety. This condition was verified during modeling in the long-term and medium-term phases of the restoration of QP in chapter 5. 4. of this study.

Despite everything, this fact forces us in further developments to solve this issue by alternative methods without violating maritime legislation.

The application of the proposed approaches was tested in terms of the use of the OLP OTG platform as an effective means for restoring the qualification parameters of operator-shipmasters (Fig. 11), which positively increased the indicators in a practical experiment with a control group.

The overall effectiveness of the full range of ship traffic management operations relying on the use of ECDIS navigation information systems during the passage of the Bosphorus increased from 64 % to 89 %, the percentage of significantly changing the ship's course in 32 % of cases, and the percentage of critical situations requiring intervention of the captain fell from 24 % to 7 %. At the same time, the total time for performing operations fell by 18 %, which indicates the saving of fuel and resources of ship systems and complexes.

The disadvantages of this study are that the proposed formalization is based on individual indicators of the operator-shipmaster in each particular situation. This forces us to be sure that the operator is in a psychophysiological state adequate to the situation, which means that s/he needs additional efforts and software and hardware computing power, appropriate mathematical methods.

The development of this research, taking into account existing mathematical complexity and limitations in the experimental part, involves the refinement of the proposed model and method, the development of individually oriented algorithms for the identification of the actions of operator-shipmasters. In turn, this direction contributed to a holistic view of maritime safety issues and the development of practical recommendations [40], which take into account the actual working conditions of shipmasters under difficult sailing conditions [41].

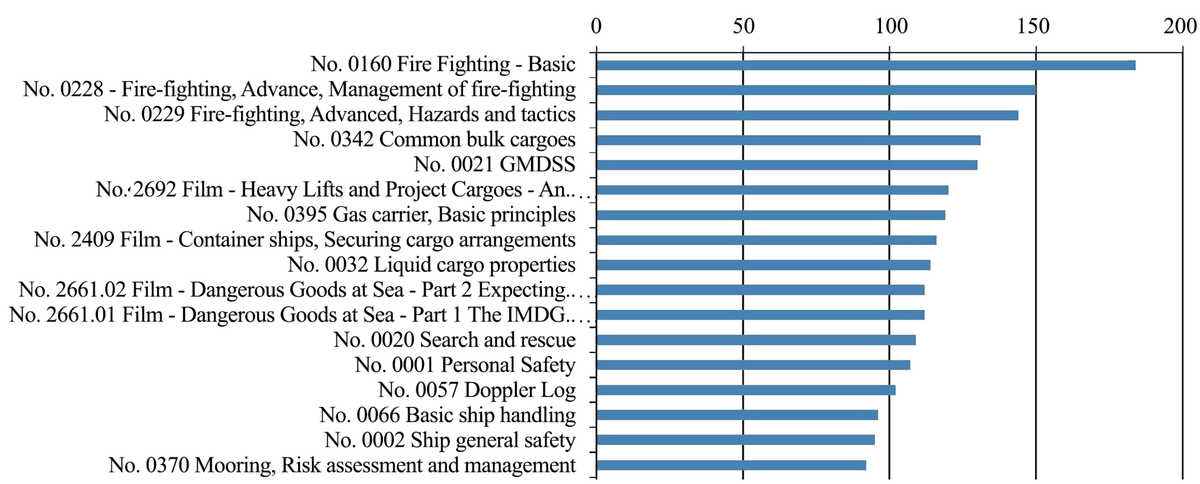

Fig. 11. Data from the OLP OTG server on the rating of marine operations

7. Conclusions

1. A model of identification of intuitive actions of operators-shipmasters in critical situations has been built, which by structure consists of 15 categories, each of which is represented in a formal-logical form. The actions of shipmasters when assessing the situation, choosing actions, their cognitive processes, when searching for resources and synthesis of time were analyzed, the influence of experience and the peculiarities of the navigation area were taken into account. Taking into account the complexity of formalizing intuitive processes in the actions of shipmasters, each category was separately structured according to a formal description, manifestation, criterion, factor, and additional explanation regarding the introduced variables.

This stage of our research made it possible to more deeply determine various aspects of the intuitive behavior of shipmasters, to bring their formal analysis closer to the elements of automation. In this sense, the support of decision-making by the shipmaster and response to navigational challenges provides the basis for the development of effective navigational safety strategies.

2. A method of restoration of qualification parameters of shipmasters based on a sequence of innovative approaches used in the process of restoration of qualification parameters of shipmasters has been devised. A key element is the application of correlation analysis and machine learning to identify and cluster behavioral patterns. So, for example, the use of graph theory for ranking helps determine the priority of various parameters in the context of navigation safety.

In addition, at this stage of the study, dynamic modeling and linear regression are performed to predict the shipmaster's reactions, which is critical for adapting the content of the restoration of shipmasters' qualification parameters. It is aimed not only at practical application but also at a theoretical basis based on a deep understanding of the cognitive processes and behavioral reactions of an individual shipmaster.

The innovation of this research is a comprehensive approach that provides not only the understanding and recovery of qualification parameters but also the ability to adapt the obtained metadata to improve the efficiency and safety of navigation operations.

3. We have constructed data processing schemes that include automated selection and submission of content containing photos and video fragments of similar navigation situations to provide a method of restoring the qualification parameters of the shipmaster. Our experiments on the Rotterdam-Amsterdam route on the basis of the proposed schemes confirmed that this approach significantly increases the confidence of shipmasters in their actions, contributing to an increase in the level of safety during navigation. According to the results of the experiment, the proposed method ensured accurate compliance with the planned course and speed, which is important for the safety of navigation in difficult navigation areas.

4. Analysis of changes in the level of danger was carried out, taking into account the time of restoration of the qualification parameters of the shipmaster, which was based on a comprehensive approach using the mathematical model built. The model made it possible to integrate data from navigation systems, in particular ECDIS, radar, gyrocompass, etc., using differential equations to predict the level of risk. It includes functions for displaying external influence, time delays in decision-making, and also evaluates the intensity of external conditions. The plots show in detail how the changes in the plan for the restoration of qualification parameters of the operator-shipmaster affect the dynamics of risk. This allows devising more effective strategies for maneuver planning, crew training, and safety system design, ensuring a high level of readiness for maritime challenges.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study and the results reported in this paper.

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Data availability

All data are available in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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