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GENERALIZED MODEL OF CONTROL OF ERGATIC NAVIGATIONAL SUPPORT SYSTEMS WITH AN INTEGRAL INDICATOR OF THE INFLUENCE OF THE HUMAN FACTOR

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The article develops a generalized model of the control of ergatic navigational support systems with an integral indicator of the influence of the navigator's human factor. The relevance of the study is determined by the need for a formalized consideration of the behavioral, cognitive-temporal, and dynamic manifestations of the navigator's activity within the contours of risk assessment, decision support, and automated control of vessel motion. The aim of the work is to construct an integrated model that combines the systemic representation of the ergatic system, the formalization of AIS/ECDIS data, the fractal-episodic representation of vessel micromotions, the cognitive-temporal states of the navigator, the gravitational-inertial interpretation of stability, and a risk-oriented control contour. The scientific novelty consists in the introduction of an integral indicator of the influence of the human factor on the increase in the risk of the ergatic navigational support system, which combines episodic behavioral, cognitive-temporal, dynamic-stability, and control-risk components into a unified information-analytical contour. The numerical approbation of the proposed indicator is intended to be carried out using the Monte Carlo method, which makes it possible to evaluate variability, sensitivity, and the probability of transition of the system to strained and critical operating modes. The practical significance of the work lies in the possibility of using the proposed model in decision support systems, the diagnostics of the navigator's state, and the automated formation of safe modes of control of vessel motion.

Key words: *ergatic system; navigational support; human factor; safety of navigation; navigator; AIS/ECDIS data; fractal-episodic analysis; integral risk indicator; automated motion control.*

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Introduction. The contemporary development of maritime transport is accompanied by an increase in shipping intensity, the complication of the navigational situation, the expansion of the use of automated and intelligent control systems, as well as higher requirements for the safety of navigation. Under such conditions, the safety of navigation is determined no longer only by the technical level of individual navigational means, but by the coherence of the functioning of an integral ergatic system in which the navigator, the vessel, the navigational and information environment, data display means, and decision-support contours form a unified functional space. For this very reason, the human factor of the navigator should be considered not as an external source of random errors, but as an internal systemic parameter that directly affects the quality of navigation situation assessment, the timeliness of the navigator's response, and the integral risk level of the functioning of the ergatic system [1, 3, 7, 9].

The analysis of contemporary scientific works shows that research in this field of knowledge is developing mainly along several interrelated but insufficiently integrated directions. The first of them covers the issues of the human factor, organizational causes of navigational errors, and approaches to the safe operation of vessels [1, 3]. The second is associated with the development of ECDIS, the assessment of its influence on the navigator's situational awareness, and the risks of excessive reliance on navigational information systems and electronic cartography [7, 9]. The third direction is focused on the use of AIS data as a source of intelligent analysis of vessel movement through the classification of their trajectories, anomaly detection, and risk assessment [2, 4, 5]. The fourth direction concerns the identification of the behavioral, cognitive, and temporal characteristics of the navigator-operator in ergatic navigational support systems, including attention analysis, subjective time distortion, prediction of the navigator's actions, and analysis of his or her functional state [6, 8, 10–12].

At the same time, most of the existing approaches remain fragmentary. Within some works, the technical-navigational or information-system aspect predominates, while within others the analysis of the human factor, qualification, attention, or risk prevails; however, there is no integral model that would combine the observed AIS/ECDIS data, the microdynamics of the trajectory, the behavioral features of the navigator's actions, the cognitive-temporal states, and the dynamics of risk change within a single analytical contour. This gives rise to the scientific problem of integrating heterogeneous layers of description – from trajectory data and features of micromovements to models of the navigator's state, his or her qualification parameters, and procedures of risk-oriented control [2, 6, 10–13].

This problem becomes especially relevant under the conditions of transition from passive recording of navigational events to the intelligent interpretation of the navigator's actions on the basis of informational control features. The availability of large volumes of AIS/ECDIS data creates prerequisites for the construction of formalized models capable not only of describing the vessel's movement trajectory, but also of revealing hidden features of micromovements, operator instability, deterioration in the quality of situation perception, and the transition of the system to strained or critical operating modes.

All this determines the necessity for a unified integral indicator that would combine behavioral, cognitive-temporal, dynamic-stability, and control-risk components within the framework of a generalized model of the ergatic navigational support system.

Analysis of recent research and publications. In research on navigation safety problems, an approach is increasingly dominating according to which automated systems are considered not in isolation, but in close connection with the human factor, the operator's cognitive workload, and the specific features of human–machine interaction. Thus, paper [14] investigates the impact of human–automation interaction in maritime operations, which emphasizes the need to assess not only technical reliability, but also the operator's ability to correctly recognize the development of potentially dangerous modes. In paper [15], the problematics of the human factor in remote ship operations are considered as interdisciplinary, with emphasis placed on issues of cognitive support, communication, and the organization of supervision. Research [16] complements this direction, as it shows that, in the transition to remote monitoring and control of autonomous unmanned vessels, the key problem remains the preservation of adequate operator situational awareness. Taken together, these works confirm that the human factor is not removed from the safety loop with the growth of automation, but, on the contrary, acquires new forms of manifestation under conditions of remote control and complex information interfaces.

A separate block of contemporary works is devoted to cooperative decision-support systems for navigators during maneuvering and collision avoidance. Paper [17] proposes a collision avoidance system specifically oriented toward human–machine cooperation in decision-making in conflict navigation situations. Paper [18] reveals this issue from the perspective of the end user, as it analyzes navigators' attitudes toward a collision avoidance decision-support system and in fact shows that the effectiveness of such solutions is determined not only by the algorithm, but also by the extent to which the system is consistent with the operator's mental model. In research [19], the collision avoidance task for autonomous ships is considered directly under conditions of human–machine cooperation, which once again emphasizes the need to integrate into safety models not only formal criteria of encounter, but also the nature of human participation in maneuver selection. Taken together, these works demonstrate a transition from purely computational schemes to interpretable cooperative approaches in which an automated decision must be understandable and acceptable to the navigator.

An important direction of recent research is connected with the explainability of artificial intelligence and the consideration of the human factor in autonomous or remotely controlled shipping systems. Paper [20] substantiates the need for human-centered explainable artificial intelligence for maritime autonomous surface vessels, that is, for an approach under which an algorithm must be not only functionally effective, but also understandable to the user. Research [21] develops a related problematic, focusing on the influence of the human factor on the safety of remotely controlled merchant vessels. Paper [22] proposes an analysis of the influence of the human–machine cooperation factor on risk in maritime transport based on historical data on errors and violations. These publications are important for the present article, since they confirm that, even under conditions of a high level of informatization and automation, navigation safety is determined not only by the technical capabilities of the system, but also by the quality of interface design, the level of trust in system decisions, and the human ability to correctly interpret the information received.

At a more generalized level, recent research is moving from the analysis of individual tasks to a systemic understanding of the safety of human–machine interaction in the maritime field. Paper [23] proposes an integrated framework for assessing the safety and efficiency of human-MASS interactions, which indicates the maturity of this direction in the contemporary international literature. Taken together, these works show that international research has already accumulated sufficient material on HMI, remote control, decision support, explainable AI, and collision avoidance.

At the same time, the unresolved part of the problem remains the construction of a unified analytical model that would combine the behavioral manifestations of the navigator, his or her cognitive-temporal states, trajectory features of vessel movement, and integral risk assessment within a single formalized contour.

Purpose and objectives of the research.

The purpose of the article is to develop a generalized model for controlling ergatic navigational support systems with an integral indicator of the influence of the navigator’s human factor.

To achieve the stated purpose, it is necessary to solve the following objectives:

– to formalize the ergatic system as a unified functional space of states;

– to present AIS/ECDIS data as an external informational image of this system;

– to identify fractal-episodic features of vessel micromotions and to integrate cognitive, temporal, and behavioral characteristics of the navigator’s activity;

– to form an integral indicator of the influence of the human factor on the increase in risk;

– to outline an approach to the numerical approbation of the proposed model by the Monte Carlo method.

Main material of the research. Thus, the relevant scientific task is to develop a generalized model for controlling ergatic navigational support systems in which the navigator’s human factor is introduced into the structure of the model as an internal parameter associated with trajectory manifestations of control, cognitive-temporal states, and changes in the risk level. Such a formulation makes it possible to move from a fragmented analysis of individual factors to a unified risk-oriented space of assessment and control.

Theoretical and methodological foundations of the generalized model.

The generalized control model should be considered as a state space:

$$E(t) = \langle X_O(t), X_V(t), X_N(t), X_R(t) \rangle \ , \tag{1}$$

where $X_O(t)$ is the state of the navigator-operator, $X_V(t)$ is the state of the vessel, $X_N(t)$ is the navigational-information environment, and $X_R(t)$ is the regulatory-situational constraints. Such a representation of the model fundamentally establishes that the navigator is not an external user of the system, but enters its internal structure as one of the key control variables.

The observable informational layer of the system is defined by the relation:

$$Y(t) = H(E(t)) + \varepsilon(t), \tag{2}$$

where $Y(t)$ is the vector of observed navigational data, $H(\cdot)$ is the operator of mapping the internal state of the ergatic system into measurable parameters, and $\varepsilon(t)$ is the observation error. In turn, AIS/ECDIS data acquire a clear methodological status: they are not the system itself, but rather its external informational image.

The conceptual-structural model of the navigator’s information field sets the context for this system formulation. The information field is considered as a multi-level, functionally ordered set of navigational, communication, procedural, spatio-temporal, and risk-oriented data that ensure the formation of a situational model of the environment, the assessment of the vessel's state, the selection of a control mode, and the monitoring of the results of implemented actions.

Thus, at the theoretical and methodological level, an integrated contour "navigator – information field – technical means – external environment – control modes" is formed. It is precisely this that determines the necessity of proceeding to the formalization of navigational observations as the analytical layer of the system.

Formalization of navigational data and construction of the analytical space.

The basic unit is not an individual AIS/ECDIS message, but a time-ordered vessel movement trajectory or its fragment corresponding to a certain control mode. It is the trajectory that preserves the causal-temporal structure of the navigation process, the sequence of micro-corrections, and local deviations from the reference line of motion.

In its minimal form, the trajectory can be represented as:

$$T_f = \left\{ \left(t_i, \varphi_i, \lambda_i \right) \right\}_{i=1}^{N_f}, \quad f \in \Phi, \tag{3}$$

where Φ is the set of vessel passages, t_i is a time stamp, φ_i, λ_i are geographic coordinates, and N_f is the number of observations.

Formally, the task of normalization and unification is represented as the mapping:

$$F^{(k)} \to S^{(k)}, \tag{4}$$

where $F^{(k)}$ is the initial INS file of the k-th passage, and $S^{(k)}$ is the unified series suitable for mathematical analysis.

The standardized trajectory series is defined as:

$$S^k = \left\{ \left(t_i, x_i, y_i, COG_i, ROT_i, XTE_i \right) \right\}_{i=1}^{N_k^*} \tag{5}$$

where t_i is time on a unified scale, (x_i, y_i) are coordinates in a local metric system, COG_i is the course, ROT_i is the angular rate of turn, and XTE_i is the cross-track deviation from the reference trajectory.

The temporal and spatial unification of data is formalized by the operators:

$$\Phi_t : Time_i \to t_i, \; t_i \in \text{sec}, \tag{6}$$

$$\Phi_{xy} : \left(Lat_i, Lon_i \right) \to \left(X_i, Y_i \right) \in \check{Y}^2 . \tag{7}$$

The methodological completeness of the unified representation is determined not only by the composition of variables, but also by the system of requirements it must satisfy. Such a system is expediently represented as:

$$\Re\left(S^{(k)} \right) = \left\{ R_t, R_s, R_c, R_d, R_q, R_i \right\}, \tag{8}$$

where R_t is the requirement of temporal unification, R_s is the requirement of spatial and metric consistency, R_c is the requirement of kinematic compatibility of motion parameters, R_d is the requirement of correctness in constructing derived features, R_q is the requirement of data quality control, and R_i is the requirement of interpretive suitability for the tasks of analyzing the navigator's actions. In this formulation, the unified series acts not merely as a data format, but as a structured environment for further analytical and intelligent processing.

As a result, a unified temporal-spatial analytical space is formed in which the observed vessel movement can already be interpreted as a carrier not only of geometric, but also of kinematic and behavioral features.

Intelligent processing of AIS/ECDIS and identification of hidden features of the navigator's actions.

The generalized model cannot be limited only to the standardized series $S^{(k)}$, since such a series by itself still does not provide an answer to the question of the structure of the navigator's local actions. For this very reason, a fractal-episodic approach is used, within which the trajectory is analyzed not as a continuous curve, but as a sequence of local episodes of micromotions with their own fractal and dynamic characteristics.

The formalization of the micromotion episodes constructed at the previous stages is as follows:

$$\varepsilon_{f,i} = \left(t_{f,i}^{start}, t_{f,i}^{end}, X_{f,i}^{peak}, Y_{f,i}^{peak}, B_{f,i}\right), \tag{9}$$

which have temporal boundaries, duration, spatial reference, and a set of fractal-dynamic characteristics.

Then, for each episode, a vector of primary fractal-dynamic features is formed:

$$z_{f,i}^{raw} = \left(h_X^{raw}, h_Y^{raw}, \mu_X^{raw}, \mu_Y^{raw}, h_R^{raw}, h_C^{raw}\right), \tag{10}$$

which constitutes the primary signature of the micromotion episode.

Next, a sample of feature values is formed:

$$\left\{z_n\right\}_{n=1}^{N} = \left\{Z\left(\varepsilon_{f,i}\right)\right\}, \tag{11}$$

after which decile binning is applied.

As a result, the six basic features of the episode are encoded by six digits, and the fractal code of the episode is defined as:

$$FC - abcdef = FC - \left(hX, hY, \mu X, \mu Y, hR, hC\right), \tag{12}$$

where $a,\ldots,f \in \{0,\ldots,9\}$ characterize the corresponding fractal-dynamic groups of features.

For the further typologization of episodes, the concept of a code family is also used:

$$family = ab \in \left\{00,\ldots,99\right\}. \tag{13}$$

In parallel with fractal coding, a continuous risk indicator is calculated for each episode. This forms the contextual component of risk and is completed by a three-level categorization into High, Medium, and Low, where:

$$High \Leftrightarrow \left(hX \ge 8 \wedge hY \ge 8 \vee hR \ge 8 \vee hC \ge 8\right) \wedge D_{f,i} \ge D_{hight}, \tag{14}$$

$$Medium \Leftrightarrow \left(hX + hY \ge 12\right) \vee \left(hR + hC \ge 12\right). \tag{15}$$

All other episodes are automatically assigned to the Low category. In its completed form, each micromotion episode is described by the triple:

$$\left(FC - abcdef, R_{f,i}^{tot}, RiskLevel_{f,i}\right). \tag{16}$$

Thus, the vessel trajectory is transformed into a behavioral-risk space in which local movement fragments become formalized carriers of features of the navigator's actions.

Integration of the cognitive, temporal, and psychophysiological states of the navigator.

The generalized model must take into account not only the external trajectory manifestations of the navigator's activity, but also the internal cognitive mechanisms that determine the distribution of attention, the temporal organization of actions, and the psychophysiological state of the operator.

The distribution of the navigator's attention is represented as a metrized space in which changes in the focus of perception are described by the metric:

$$ds^2 = e^2 dR^2 - a^2 d\theta^2 + \sin^2\theta\left[d\psi^2 + \sin^2 R d\tau^2\right]. \tag{17}$$

At the same time, the complexity of the navigational situation lies in the fact that all υ_i are independent of one another and cannot be mutually substituted:

$$v\left\{f : f \in F, (x,y,z) \in f\left(\upsilon_1\right), \ldots, (x,y,z) \in f\left(\upsilon_n\right)\right\} = \prod_{i=1}^{n} p_{(x,y,z)}\left(\upsilon_i\right) \tag{18}$$

Let the tendency in the 3D space of alternatives be denoted as P_j, where $j = 1,...,|\Re|$; then the tendency along the *x*-axis, "vision," will take the form:

$$X_j(x,y,z) = \begin{cases} \lambda \subset [0,5;1], \ if \ (x,\bar{y},\bar{z}) \in P_j, \\ 1-\lambda, \ if \ (\bar{x},y,z) \in P_j, \\ 0, \ if \ (x,y,z) \notin P_j. \end{cases} \tag{19}$$

where the probability that the attention object υ_i will have the tendency is P_j:

$$p_j(\upsilon_i) = v\{f : f \in F, \ f(\upsilon_i) = P_j\}. \tag{20}$$

Then the generalized model for all objects and individual tendencies of perception will take the form (21):

$$p_{(x,y,z)}(\upsilon) = \sum_{j=1}^{|\Re|} X_j(x,y,z)\, p_j(\upsilon). \tag{21}$$

It follows from this model that, under conditions of an insufficient level of training, overload, or excessive complexity of the navigational situation, complete coverage of all attention objects becomes unlikely.

To describe the temporal organization of the operator cycle, a Markov approach is used. The probability of transition between temporal states is defined as:

$$P\{S(t+\Delta t) = s_j \mid S(t) = s_i\} = p_{ij}(\Delta t), \tag{22}$$

and the evolution of the probabilities of these states is described by the Kolmogorov equations:

$$\frac{dp_i(t)}{dt} = \sum_{j \neq i} p_j(t)\lambda_{ji} - p_i(t)\sum_{j \neq i} \lambda_{ij}. \tag{23}$$

The interrelated quantities $\xi_1,...,\xi_n$ are represented through the corresponding relation of the measure of possibility:

$$\begin{aligned} \mu_{\xi_1,...,\xi_n}(x_1,...,x_n) &= \pi\{\gamma \in \Gamma : \xi_1(\gamma) = x_1,...,\xi_n(\gamma) = x_n\} = \\ &= \pi\{\xi_1^{-1}(x_1) \cap ... \cap \xi_n^{-1}(x_n)\}, \ \forall (x_1,...,x_n) \in R^n \end{aligned} \tag{24}$$

where π is the measure of possibility,
Γ is the set of elements of the system,
R is the modal value of the possibility of the quantity,
γ is an atomic element of the system.

To normalize the quantities $\xi_1,...,\xi_n$, the criterion α is introduced, which is interpreted as the level of risk of erroneous distribution of the estimate. Accordingly, the form of the distribution of possible polar quantities *H(x)* under the conditions of the fuzziness coefficient b' relative to the investigated parameter a', which characterizes the manifestation of subjective time distortion, is described by the relations:

$$b' = \frac{\max\limits_{1 \le i \le n} x_i - \min\limits_{1 \le i \le n} x_i}{H_+^{-1}(\alpha) - H_-^{-1}(\alpha)}, \tag{25}$$

$$a' = \frac{1}{2}\left(\max_{1 \le i \le n} x_i - \min_{1 \le i \le n} x_i\right) + \frac{b'}{2}\left(H_+^{-1}(\alpha) - H_-^{-1}(\alpha)\right) \tag{26}$$

The cognitive-temporal block is completed by models of critical situations, contextual similarity, and *p*-adic complexity of the situation. For this purpose, in particular, the representation is used:

$$x = \alpha_0 + \alpha_1 p + ...\alpha_{n-1} p^{n-1}, \tag{27}$$

which corresponds to the *p*-adic description of the level of structural complexity of perception.

Depending on the value of the degree of similarity, a logical relation arises between the current situation *β* and the situation α\alphaα that is the closest in context and in the degree of past experience. Then the comparison of the two closest situations is defined as:

$$\mathrm{Sim}\left(\alpha,\beta \mid \{\tau / T\}\right) = \left|\{\underline{\tau} / T\}_\alpha \cap \{\underline{\tau} / T\}_\beta\right| / \left|\{\tau\}\right|, \tag{28}$$

where *τ* is the terminal element of experience with respect to the operation being performed.

Further, it should be determined that the lower the threshold of the emotional surge of situation *β*, the more difficult it is to identify a coincidence with situation *α*, taking into account that:

$$\forall\alpha,\beta \;\; if \;\; \{\tau / T\} \le \{\tau / T'\} \Rightarrow 0 \le \mathrm{Sim}\left(\alpha,\beta \mid \{\tau / T\}\right) \le \mathrm{Sim}\left(\alpha,\beta \mid \{\tau / T'\}\right) \le 1. \tag{29}$$

It is clear that, depending on the completeness of $\{G(\tau)\}$, the possibility arises of determining the maximum convergence of *α* and *β*:

$$\mathrm{Sim}\left(\alpha,\beta \mid \{G(\tau)\}\right) = \max_{\{\tau/T\}^\wedge} \mathrm{Sim}\left(\alpha,\beta \mid \{\tau / T\}\right), \;\; M = \prod_{\tau\in\{\tau\}} \left|\left[G(\tau)\right]\right|, \tag{30}$$

where *M* is the quantity of similarity, and $\{\tau / T\}^\wedge$ is the set of terminal domains.

Thus, there is a probability of an increase in the risk of maritime catastrophes due to the absence of the factor of “distinguishing” two situations $\{\tau / T\}_\alpha \approx \{\tau / T\}_\beta$. The only possible distinguishing feature remains the context of the situation with emotional bursts close in their intensity:

$$K^{em} = \left\langle \Omega(Z), \{G(\tau)\}, \{S\} \right\rangle, \tag{31}$$

then:

$$\mathrm{Con}\left(\alpha,\beta \mid K^{em}\right) = 1 \Leftrightarrow z_\alpha = z_\beta, \text{ else } \mathrm{Con}\left(\alpha,\beta \mid K^{em}\right) < 1, \tag{32}$$

where *S* is the set of formed experienced reactions.

In this form, the internal states of the navigator acquire a formalized status and can be included in procedures for risk assessment and the selection of a control mode.

Formalization of the influence of the human factor on the stability, unsteadiness, and risk of the ergatic system.

The proposed gravitational-inertial model, introducing a direct physical-analog representation of the human factor through the position of the internal center of gravity along the system axis, serves as the basic foundation for the analysis of the controlled dynamics of the navigational contour in the ergatic system.

Let us introduce the normalized coordinate of the center of gravity of the human factor:

$$z_h(t) \in [0,1], \tag{33}$$

where $z_h(t) \to 0$ corresponds to the most stable functional state of the navigator, and $z_h(t) \to 1$ to the most destabilizing one.

The normative restoring moment is defined as:

$$M_N(\theta,t) = mG(t) l \sin\theta, \tag{34}$$

and the internal destabilizing moment of the human factor as:

$$M_H(\theta,t) = m_h g_h z_h(t)\sin\theta . \tag{35}$$

The resulting moment of the system is determined by the relation:

$$M_\Sigma(\theta,t) = M_{ext}(t) + M_H(\theta,t) - M_N(\theta,t), \tag{36}$$

and the angular dynamics of the system is described by the equation:

$$J_\theta\theta'' + c_\theta\theta' = M_\Sigma(\theta,t), \tag{37}$$

$$J_\theta\theta'' + c_\theta\theta' = M_{ext}(t) + \left(m_h g_h z_h(t) - mG(t)l\right)\sin\theta . \tag{38}$$

For small angles of deviation, when $\sin\theta \approx \theta$, the linearized form becomes:

$$J_\theta\theta'' + c_\theta\theta' + k_{eff}(t)\theta = M_{ext}(t) . \tag{39}$$

The effective angular stiffness of the system is defined as:

$$k_{eff}(t) = mG(t)l - m_h g_h z_h(t), \tag{40}$$

and the critical position of the center of gravity of the human factor is given by the relation:

$$z_{h,crit}(t) = \frac{mG(t)l}{m_h g_h}, \tag{41}$$

while the relative stability margin is:

$$\mu_{st}(t) = \frac{k_{eff}(t)}{mG(t)l} . \tag{42}$$

Further accounting for the degradation of the functional resources of the system is carried out through the parameters:

$$I_{3,eff}(t) = I_{3,0}\left(1 - \alpha_I z_h(t)\right), \tag{43}$$

$$\omega_{3,eff}(t) = \omega_{3,0}\left(1 - \alpha_\omega z_h(t)\right), \tag{44}$$

$$L_{eff}(t) = I_{3,eff}(t)\,\omega_{3,eff}(t), \tag{45}$$

and the frequency of forced corrections is described as:

$$\Omega(t) = \frac{M_{dem}(t)}{L_{eff}(t)} . \tag{46}$$

Then the integral manifestation of risk can be represented as a normalized logistic function:

$$R(t) = \sigma\left(a_0 + a_1\left|\theta(t)\right| + a_2\left|\theta'(t)\right| + a_3\Omega(t) + a_4\left(1 - \mu_{st}(t)\right)\right), \tag{47}$$

where $R(t) \in [0,1]$ is the integral risk level; $\sigma(\cdot)$ is the logistic normalization function; $a_0,\ldots,a_4$ are the calibration parameters of the model.

In this formulation, the human factor enters the integral dynamics of the ergatic system as an internal destabilizing parameter, which makes it possible to move from a qualitative description of fatigue, tension, or overload to a formal mechanism of changes in stability and risk.

Risk-oriented control contour and applied output into automated modules.

The final level of the generalized model is the transition from the assessment of states and risk to the formation of control actions. This contour is unfolded through the p-adic structuring of the situation, multicriteria risk functionals, admissible control domains, automated multi-target collision avoidance, and the storm subcontour.

At the level of the p-adic description of the situation, the following representation is used:

$$\lim_{n\to\infty} p^n y = x, \quad y \in Z_p, \tag{48}$$

and the function of generating the next point:

$$f_s(x) = x^s, \ \ s = 2,3,...,n\,. \tag{49}$$

This makes it possible to transition to the nearest *p*-adic systems along an ascending or descending trajectory depending on the situation:

$$\mathbf{U}(\tau) = \left[\cap_{j=1,...,n} Gv^{\uparrow}\left(\tau | a_j\right)\right]. \tag{50}$$

At the same time, the transition process is symmetric regardless of direction:

$$Gv^{\downarrow}(\tau|b) = Gv^{\uparrow}(\tau|a) \Rightarrow \langle \underline{\tau}, P\rangle_W \text{ при } Gv^{\uparrow}\left(\tau|a_i\right) \cap Gv^{\uparrow}\left(\tau|b_i\right) = \varnothing\,. \tag{51}$$

Proceeding from the proposed relations, it can be assumed that there exists a certain balance of *p*-adicities for which the following holds to an equal extent:

$$\begin{gathered} \forall x \in \left[Gv(\tau)\right] \Rightarrow \exists a \in \{a\}, \\ x \in \left[Gv^{\uparrow}(\tau|a)\right] \& \exists b \in \{b\}, x \in \left[Gv^{\downarrow}(\tau|b)\right]. \end{gathered} \tag{52}$$

Thus, the observed balance of transition to p-adic structures may depend both on the factors of the level of complexity of the navigational situation (necessity) and the level of qualification of the navigator (possibility):

$$Gv(\tau) = \cup_{a\in\{a\}} Gv^{\uparrow}(\tau|a) = \cup_{b\in\{b\}} Gv^{\uparrow}(\tau|b)\,. \tag{53}$$

Based on the previously considered approaches and formal descriptions, a method for diagnosing the perception of the navigational situation is proposed, based on the accepted theory of *p*-adic systems and the metric: $\rho_p(x,y) = |x-y|_p\,, x \to |x|_p\,.$

The complexity of the situation requires from the navigator an appropriate level of perception, each of which can be expressed by the spaces $(X,\rho) \vee (Y,\rho')$. Thus, for example, decision-making in binary logic (p = 2) most closely corresponds to simple tasks requiring the switching on or off of the navigator's attention according to specified features. In turn, (p = 3) adds a linguistic variable according to the principle:

$$\rho'\left(j\left(x_{1_{p=2}}\right), j\left|x_{2_{p=2}}\right|\right) = \rho\left(x_{1_{p=3}}, x_{2_{p=3}}\right)\,, \tag{54}$$

and transfers it to a higher level. This means that tasks solved in space *Y* cannot be solved in space *X*. This process can be formally described using the term "subjective entropy" H_π:

$$H_\pi = -\sum_{i=1}^{N} \pi(\sigma_i) \cdot \ln \pi(\sigma_i), \tag{55}$$

Further, risk is considered as a controlled object. For this purpose, the condition of motion without an increase in risk is introduced:

$$\frac{d}{dt}\rho(p,t) = \nabla\rho(p,t)\cdot p'(t) + \frac{\partial\rho}{\partial t} = 0\,, \tag{56}$$

and in the quasi-stationary case:

$$\nabla\rho(p,t)\cdot p'(t) = 0\,. \tag{57}$$

For the multicriteria assessment of control quality, a vector functional is used:

$$J(x,u) = \begin{bmatrix} \int C_1\left(x(t),u_1(t)\right)dt \\ \int C_2\left(x(t),u_2(t)\right)dt \\ ... \\ \int C_m\left(x(t),u_m(t)\right)dt \end{bmatrix}, \tag{58}$$

and a penalty functional of manual interventions:

$$C_H = \beta_1 + \beta_2 \int u_{H \neq 0}^2 (t) dt . \quad (59)$$

Threshold constraints on the quality components or aggregated risk are specified by the formula:

$$C_i \leq C_i^{perm}, \ or \ \sum \alpha_i C_i \leq R_P^{perm} \quad (60)$$

Since in real vessel traffic the problem has a multicriteria nature (interaction with a set of targets/vessels), it is expedient to use the target vector in the form:

$$s(x) = \begin{bmatrix} S_1(x) \\ S_2(x) \\ \dots \\ S_n(x) \end{bmatrix}, \quad (61)$$

which reflects the set of performance criteria that must be coordinated. To reinforce the consistency of the goals, a condition is applied that reflects the absence of mutual sensitivity of the criteria:

$$\frac{\partial C_i}{\partial C_j} = 0, \ i \neq j \quad (62)$$

The formal formulation of the optimization problem under safety constraints is implemented through the Lagrangian construction and the Kuhn–Tucker conditions, where the Lagrange multipliers acquire the meaning of the "tension" of the vessel motion control process with respect to risk and resource constraints:

$$L(x, \lambda) = \lambda_0 S(x) - \lambda_1 \varphi_1(x) - \lambda_2 \varphi_2(x), \ \nabla_x L(x, \lambda) = 0, \quad (63)$$

where $\varphi_1(x)$ may represent the risk corridor constraint $\rho(p, t) \leq \rho_A$, and $\varphi_2(x)$ may represent the constraint on dangerous approaches/intersections of risk domains. The implementation of the "onboard controller cycle," as a continuous mechanism for tracking risk, is formalized through the formulation of optimal control on an interval and the use of the Hamiltonian:

$$\left(x^*, u^*, t^*\right) \to \text{extr} \int_{t_0}^{t_1} F(x, u, t) dt, \ x' = f(x, u, t), \quad (64)$$

with the Lagrangian functional:

$$L^* = \int_{t_0}^{t_1} \left[f_0 \lambda_0 + \lambda^T f - \lambda^T x' \right] dt = \int_{t_0}^{t_1} L(x, x', u, \lambda) dt , \quad (65)$$

and the decomposition:

$$L(x, x', u, \lambda) = H(x, u, \lambda) - \lambda^T x' . \quad (66)$$

The optimality conditions in the controller contour may be represented as the choice of control by the navigator that minimizes the Hamiltonian at each step:

$$u^*(t) \in \arg \min_{u \in U} H(x(t), u, \lambda(t)), \ \frac{\partial H}{\partial u} = 0, \quad (67)$$

together with the relations for the state and conjugate variables:

$$x' = \frac{\partial H}{\partial \lambda}, \ \lambda' = -\frac{\partial H}{\partial x}. \quad (68)$$

The practical output into automated multi-target collision avoidance is implemented through admissible control domains. For each *j*-th target, the following is specified:

$$\Omega_j = \left\{ (V, K) \mid \Delta V_j^T (V, K) \in SDC_j \right\}, \quad (69)$$

and the general admissible control domain is defined as:

$$\Omega = \bigcap_{j=1}^{N_g} \Omega_j \,. \tag{70}$$

The deficit of safe actions is estimated by the indicator:

$$\rho(t) = 1 - \frac{\mu(\Omega(t))}{\mu(\Omega_0)}, \ \ \rho(t) \in [0,1], \tag{71}$$

and the target function for maneuver selection is written in the form:

$$J(V,K) = w_s \rho(t) + w_r \left|K - K_{plan}\right| + w_v \left|V - V_{plan}\right| + w_u U_{man}(V,K). \tag{72}$$

Another applied completion of the model is the storm subcontour, where the “imaginary” wave period is used:

$$\tau = \frac{\lambda}{1.25\sqrt{\lambda} + 0.514V\cos q}, \tag{73}$$

and the conditions of resonance-dangerous modes: $0.7T_B \le \tau \le 1.3T_B,\ 0.7T_L \le \tau \le 1.3T_L$

The PID-like law for forming the rudder angle δ to achieve the desired course K^* and the normalized speed control command θ are given as follows:

$$\delta = k_\Psi \cdot \left(\Psi_m - K^*\right) + k_\omega \cdot \omega_m + k_f \cdot \int \left(\Psi_m - K^*\right) dt, \qquad \theta = (\pi/2) \cdot \left(V^*/V_{\max}\right). \tag{74}$$

where Ψ_m and ω_m are the measured course and angular velocity, and $V_{\max}$ is the maximum permissible speed under current conditions. These equations close the contour “assessment of the risk state – choice of response – execution – repeated assessment,” which constitutes the content of operational risk management.

Unlike the manual interpretation of diagrams, the risk factor is calculated automatically in the contour of the onboard controller and is used as a criterion for monitoring the execution of the storm scenario.

In this sense, the functioning of the system should be described as a closed contour with a control object model and a measurement channel, where the general form of the vector model is described as:

$$\frac{dX}{dt} = f\left(X, U, W, T_B, T_L\right),\ X_m = CX + \varsigma,\ U = F\left(X_m, X^*\right),\ X^* \in \bar{\Omega}. \tag{75}$$

Here, X is the state vector (speed, course, angular velocity, etc.), U is the control inputs, W is the external disturbances (wave, wind), X_m is the measured state, C is the measurement matrix, ς is the measurement error/noise, $\bar{\Omega}$ is the domain of nonresonant (admissible) modes, and X^* is the program (target) mode.

As a result, the generalized model extends not only into the plane of diagnostics and assessment, but also into the real contours of the automated formation of a safe vessel motion mode under normal and difficult conditions.

Integral indicator of the influence of the human factor on the increase in the risk of the ergatic navigational support system and its numerical approbation by the Monte Carlo method.

A logical stage in summarizing the research results is the construction of an integral indicator that combines the already formed levels of description: the systemic representation of the ergatic system, the formalization of AIS/ECDIS data, the fractal-episodic interpretation of vessel micromotions, models of the cognitive and temporal states of the navigator, the gravitational-inertial model of stability and risk, and risk-oriented control contours. As noted above, the human factor of the navigator should be considered not as a random external disturbing influence, but as an internal parameter of the ergatic system that determines the completeness of situation perception, the quality of danger assessment, the timeliness of reactions, the choice of control actions, and the integral level of vessel motion safety. This creates the basis for the introduction of a new integral indicator of a higher level of generalization.

Within the framework of this research, an integral indicator of the influence of the human factor on the increase in the risk of the ergatic navigational support system is proposed:

$$I_{HF \to R}(t) \in [0,1], \tag{76}$$

which is interpreted as a normalized estimate of the total risk-generating influence of the navigator's actions, states, and internal dynamics on the functioning of the ergatic navigational contour at time *t*.

Structurally, this indicator must combine four groups of factors: the episodic behavioral factor $E(t)$, the cognitive-temporal factor $C(t)$, the dynamic-stability factor $S(t)$, and the control-risk factor $U(t)$. Such a decomposition corresponds to the directions of the research: fractal-episodic analysis forms the behavioral features of micromotions; then formalized cognitive, temporal, *p*-adic, and entropic characteristics are introduced; the gravitational-inertial model provides a dynamic mechanism for the transition from the navigator's state to a decrease in stability; and, at the final stage, a risk-oriented contour for the selection of control actions is formed.

The basis of the integral model is expediently represented in a logistic-normalized form:

$$I_{HF \to R}(t) = \sigma \begin{pmatrix} \theta_0 + \theta_E E(t) + \theta_C C(t) + \theta_S S(t) + \theta_U U(t) + \theta_{EC} E(t) C(t) + \\ + \theta_{CS} C(t) S(t) + \theta_{SU} S(t) U(t) + \theta_{EU} E(t) U(t) \end{pmatrix}, \tag{77}$$

where $\sigma(x) = (1 + e^{-x})^{-1}$ is the logistic normalization function; θ_0 is the basic shift; θ_E, θ_C, θ_S, $\theta_U \geq 0$ are the coefficients of pairwise interaction. Unlike a simple linear sum, such a structure takes into account the amplification effect, when the simultaneous growth of several unfavorable factors brings the system into a strained or critical mode faster than would follow from the independent influence of each of them.

The first component, the episodic behavioral factor $E(t)$, is built on the results of fractal-episodic analysis of AIS/ECDIS trajectories. For this purpose, a vector of primary fractal-dynamic features of the episode is introduced:

$$z_{f,i}^{raw} = \left(h_X^{raw}, h_Y^{raw}, \mu_X^{raw}, \mu_Y^{raw}, h_R^{raw}, h_C^{raw}\right), \tag{78}$$

as well as decile coding and the *FC-abcdef* code, which makes it possible to move from a continuous description of the track to a compact formal representation of local micromotions. In addition, a continuous full episodic risk $R_{f,i}^{tot}$ and its categorization into High–Medium–Low have been constructed. Therefore, it is natural to define the aggregated episodic factor as the weighted mean of the full episodic risk within the analyzed time window $\Omega(t)$:

$$E(t) = \frac{\sum_{i \in W(t)} \gamma_i R_{f,i}^{tot}}{\sum_{i \in W(t)} \gamma_i}, \tag{79}$$

where γ_i is the weight of the *i*-th episode. To take into account the duration, turning intensity, and danger category, we set:

$$\gamma_i = 1 + \eta_D \bar{D}_{f,i} + \eta_\omega \bar{\omega}_{rms,i} + \eta_H 1_{High,i} + \eta_M 1_{Medium,i}, \tag{80}$$

where $\bar{D}_{f,i} \in [0,1]$ is the normalized duration of the episode; $\bar{\omega}_{rms,i} \in [0,1]$ is the normalized RMS of the angular velocity; $\mathbf{1}_{High,i}$ and $\mathbf{1}_{Medium,i}$ are indicators of belonging to the risk categories; η_D, η_ω, η_H, $\eta_M \geq 0$ are coefficients of significance. In such a formulation, $E(t)$ reflects not merely the average risk of local episodes, but the integrated behavioral instability of control. The construction of this factor directly relies on the fractal-episodic apparatus, including the features $z_{f,i}^{raw}$, the *FC-abcdef* code, and the categorization of episodic risk.

The second component, the cognitive-temporal factor $C(t)$, must aggregate such elements of formalization as: the model of attention distribution, the temporal states of the operator cycle, subjective time distortion, the p-adic complexity of the situation, and subjective entropy. For this purpose, the following relation is proposed:

$$C(t) = \alpha_A A(t) + \alpha_T T(t) + \alpha_D D(t) + \alpha_P P(t) + \alpha_H H(t), \qquad (81)$$

where $\alpha_A, \alpha_T, \alpha_D, \alpha_P, \alpha_H \geq 0$, $\alpha_A+\alpha_T+\alpha_D+\alpha_P+\alpha_H = 1$.

Here, $A(t) \in [0,1]$ is a normalized indicator of attention deficit or imbalance, which is formed on the basis of the model of its distribution in metric space; $T(t) \in [0,1]$ is an indicator of temporal instability, based on the probabilities of temporal states and the intensities of transitions between them; $D_\tau(t) \in [0,1]$ is an indicator of subjective time distortion; $P(t) \in [0,1]$ is an indicator of the p-adic complexity of the current situation; $H_s(t) \in [0,1]$ is an indicator of subjective entropy. Such a structure makes it possible to combine into one scalar parameter those cognitive and temporal mechanisms that are mathematically formalized separately – through the metric of attention space, Markov transitions between temporal states, fuzzy relations of subjective time distortion, the p-adic representation of situation complexity, and models of subjective entropy.

The third component, the dynamic-stability factor $S(t)$, is based on the updated gravitational-inertial model, where the human factor is introduced through the coordinate of the center of gravity $z_h(t)$, which affects the effective angular stiffness $k_{eff}(t)$, the critical boundary $z_{h,crit}(t)$, the relative stability margin $\mu_{st}(t)$, the effective characteristics $I_{3,eff}(t)$, $\omega_{3,eff}(t)$, the reserve $L_{eff}(t)$, the frequency of forced corrections $\Omega(t)$, and the integral risk $R(t)$. On this basis, the following is proposed:

$$S(t) = \beta_z \bar{z}_h(t) + \beta_\mu \left(1 - \mu_{st}(t)\right) + \beta_L \left(1 - \bar{L}_{eff}(t)\right) + \beta_\Omega \bar{\Omega}(t) + \beta_R \bar{R}(t), \qquad (82)$$

where $\beta_z, \beta_\mu, \beta_L, \beta_\Omega, \beta_R \geq 0$, $\beta_z + \beta_\mu + \beta_L + \beta_\Omega + \beta_R = 1$.

Here, $\bar{z}_h(t) = \min\left\{1, z_h(t) / z_{h,crit}(t)\right\}$ is the normalized position of the center of gravity of the human factor relative to the stability boundary; $\mu_{st}(t)$ is the relative stability margin; $\bar{L}_{eff}(t) \in [0,1]$ is the normalized reserve of stable functioning; $\bar{\Omega}(t) \in [0,1]$ is the normalized frequency of forced corrections; $\bar{R}(t) \in [0,1]$ is the normalized integral risk of the dynamic layer.

Thus, $S(t)$ reflects no longer potential, but actual intrasystem destabilization caused by the human factor. The expediency of this approach is confirmed by simulation modeling, where, when moving from a low to a high position of $z_h(t)$, a consistent decrease in k_{eff}, μ_{st}, L_{eff}, and an increase in Ω and R, are observed, which corresponds to the transition from a stable mode to a limiting high-risk mode.

The fourth component, the control-risk factor $U(t)$, must reflect no longer internal states, but the consequences of their influence on the space of admissible decisions and the “cost” of control. For this purpose, the risk field $\rho(p,t)$, the condition of motion without an increase in risk, the vector quality functional, the penalty functional of manual interventions, the admissible control domains Ω_j, Ω, the indicator of deficit of safe actions $\rho(t)$, and the objective function $J(V,K)$ are introduced. On this basis, the following is proposed:

$$U(t) = \lambda_\rho \rho_\Omega(t) + \lambda_J \bar{J}(t) + \lambda_H \bar{C}_H(t), \qquad (83)$$

where $\lambda_\rho, \lambda_J, \lambda_H \geq 0$, $\lambda_\rho + \lambda_J + \lambda_H = 1$.

Here, $\rho_\Omega(t)$ is the deficit of safe actions; $\bar{J}(t) \in [0,1]$ is the normalized integral control functional; $\bar{C}_H(t) \in [0,1]$ is the normalized intervention penalty. For $\rho_\Omega(t)$, the existing relation is used:

$$\rho_\Omega(t) = 1 - \frac{\mu\left(\Omega(t)\right)}{\mu\left(\Omega_0\right)}, \qquad (84)$$

where $\Omega(t)$ is the current admissible control domain, Ω_0 is the reference domain under a favorable mode, and $\mu(\cdot)$ is the measure of the admissible action domain. Such a factor makes it possible to assess the extent to which the influence of the human factor has already led to an actual narrowing of the safe maneuvering space.

For the numerical approbation and calibration of the integral indicator, a vector of uncertain parameters is introduced:

$$\Theta = (\theta_0, \theta_E, \theta_C, \theta_S, \theta_U, \theta_{EC}, \theta_{CS}, \theta_{SU}, \theta_{EU}, \alpha, \beta, \lambda, \eta, a_0,\ldots,a_4), \tag{85}$$

as well as a vector of random or scenario-dependent input variables:

$$X_t = \left(R_{f,i}^{tot}, D_{f,i}, \omega_{rms,i}, A, T, D_\tau, P, H_s, z_h, M_{ext}, M_{dem}, \rho_\Omega, J, C_H\right)_t \tag{86}$$

Here, Θ covers the weighting coefficients of the integral indicator, the degradation coefficients, and the parameters of logistic functions, whereas X_t combines random or semi-random variables that, in a specific time window, characterize episodic risks, cognitive-temporal states, dynamic stability parameters, and control conditions. For the weighting coefficients α, β, λ, it is expedient to use Dirichlet distributions, which automatically ensure non-negativity and a sum equal to one. For the interaction parameters θ, truncated normal or lognormal distributions are appropriate. For $z_h(t)$, a Beta distribution or a truncated normal law on [0,1] is appropriate. For episodic risks $R_{f,i}^{tot}$, durations $D_{f,i}$, and *RMS* values, it is expedient to use an empirical approach based on a real sample of AIS/ECDIS episodes, which preserves the structural specificity of the data. For M_{ext} and M_{dem}, a truncated normal or lognormal distribution is appropriate, depending on the nature of the scenario.

Calibration of the parameters of the integral model is proposed to be performed as the task of minimizing the mismatch functional:

$$\hat{\Theta} = \arg\min_{\Theta} L\left(\Theta\right), \tag{87}$$

where

$$L\left(\Theta\right) = \kappa_1 L_{elips} + \kappa_2 L_{dyn} + \kappa_3 L_{ctrl} + \kappa_4 Reg\left(\Theta\right) \quad , \ \kappa_1,\ldots,\kappa_4 \geq 0, \sum \kappa_i = 1 \tag{88}$$

Here, Λ_{epis} is the episodic component of the functional, Λ_{dyn} is the dynamic-stability component, Λ_{ctrl} is the control-risk component, and $Reg(\Theta)$ is the regularization of parameters.

The episodic component may be specified as:

$$L_{elips} = \sum_t \left(I_{HF\to R}\left(t\right) - y_t'\right)^2, \tag{89}$$

where y_t' is a weakly labeled target estimate formed on the basis of the share of High–Medium episodes, the average episodic risk, and the spatial concentration of risk peaks in the window $\Omega(t)$. This is consistent with the constructed apparatus of local coding and categorization of episodes. The dynamic calibration component is specified as:

$$L_{dyn} = \sum_{s\in\{stab,tense,crit\}} \left\|\overline{q}_s^{MC}\left(\Theta\right) - q_s^{ref}\right\|_2^2, \tag{90}$$

where q_s^{ref} are reference vectors for the stable, strained, and critical modes, and $\overline{q}_s^{MC}\left(\Theta\right)$ are the corresponding mean values obtained by the Monte Carlo method. As q_s^{ref}, it is expedient to use scenario values for the low, medium, and high position of the center of gravity of the human factor. The control-risk component is specified as:

$$L_{ctrl} = \sum_t \left[\omega_1\left(\rho_\Omega^{MC}\left(t\right) - \rho_\Omega^{obs}\left(t\right)\right)^2 + \omega_2\left(\overline{J}^{MC}\left(t\right) - \overline{J}^{obs}\left(t\right)\right)^2 + \omega_3\left(\overline{C}_H^{MC}\left(t\right) - \overline{C}_H^{obs}\left(t\right)\right)^2\right] \tag{91}$$

where $\omega_1, \omega_2, \omega_3 \geq 0$, $\omega_1 + \omega_2 + \omega_3 = 1$. For regularization, the following is used:

$$Reg\left(\Theta\right) = \left\|\Theta\right\|_2^2. \tag{92}$$

Taken together, this ensures calibration of the integral indicator not according to an arbitrary criterion, but simultaneously according to behavioral, dynamic, and applied characteristics of risk.

After calibration of the parameters, a series of Monte Carlo runs is performed. At each run $m = 1,\dots,N$, $\Theta^{(m)}$ and $X_t^{(m)}$ are generated, $E^{(m)}(t)$, $C^{(m)}(t)$, $S^{(m)}(t)$, $U^{(m)}(t)$ are computed, and then the integral indicator $I^{(m)}_{HF\to R}(t)$. Based on the results of these runs, the following statistics are estimated:

$$\mathrm{E}\left[I_{HF\to R}(t)\right],\ Var\left[I_{HF\to R}(t)\right],\ Q_{0.05}(t),\ Q_{0.5}(t),\ Q_{0.95}(t), \tag{93}$$

where E[·] is the mathematical expectation, Var[·] is the variance, and $Q_{0.05}$, $Q_{0.50}$, $Q_{0.95}$ are the quantiles of the distribution. These characteristics make it possible not to be limited to a point estimate of the integral indicator, but to analyze its variability and confidence bounds under given scenario and parametric uncertainties.

For the analysis of transitions between functioning modes, it is expedient to introduce two thresholds τ_1 and τ_2, which separate the stable, strained, and critical modes:

$$P_{stab}(t) = P\left(I_{HF\to R}(t) < \tau_1\right), P_{tense}(t) = P\left(\tau_1 \le I_{HF\to R}(t) < \tau_2\right), P_{crit}(t) = P\left(I_{HF\to R}(t) \ge \tau_2\right). \tag{94}$$

Then the Monte Carlo method provides not only the mean estimate of the index, but also the probability that the system is in or will transition into each of the modes. This is especially important for the early detection of pre-critical states and the selection of the corresponding response mode.

To determine the dominant factors, it is expedient to apply global sensitivity analysis. For each input parameter X_j, the first sensitivity index is defined as:

$$S_j = \frac{Var_{X_j}\left(\mathrm{E}\left[I_{HF\to R} \mid X_j\right]\right)}{Var\left(I_{HF\to R}\right)}. \tag{95}$$

Such an assessment makes it possible to quantitatively rank the contribution of individual factors – the episodic risk of micromotions, attention deficit, subjective time distortion, p-adic complexity of the situation, the coordinate $z_h(t)$, the stability margin μ_{st}, or the deficit of admissible actions $\rho\Omega$ – to the formation of the integral indicator.

Thus, the proposed model forms a holistic deterministic-probabilistic contour for assessing the influence of the human factor on the increase in the risk of the ergatic navigational support system. Unlike local estimates, it combines fractal-episodic features of micromotions, cognitive-temporal and psychophysiological states of the navigator, dynamic stability parameters of the gravitational-inertial model, and control-risk characteristics of the domain of admissible actions. In this case, the use of the Monte Carlo method performs not the role of a source of the model structure, but the role of an instrument for its numerical approbation, parameter calibration, robustness analysis, sensitivity analysis, and estimation of the probability of the system's transition from a stable mode to strained and critical modes of functioning. It is precisely this that makes the proposed approach suitable both for the theoretical generalization of the research results and for further implementation in decision-support systems and automated control of human-factor risks in ergatic navigational support systems.

The constructed generalized model differs fundamentally from approaches in which the human factor is taken into account only as a source of post factum error or as an external constraint of the technical system. Within the proposed structure, the human factor enters the model in two interrelated forms: as a source of observable behavioral-trajectory manifestations recorded in AIS/ECDIS data and transformed into fractal-episodic signatures, and as an internal dynamic parameter that directly changes the stability, unsteadiness, and risk of the system's functioning through the gravitational-inertial model.

The second strong point of the model is that it does not end at the diagnostic stage. Owing to the p-adic description of the situation, risk functionals, domains of admissible control actions, and the storm subcontour, the model passes directly into procedures for the automated selection of safe actions. Therefore, the article may be positioned not as a description of individual mathematical tools, but as a holistic ergatic concept of navigational support management with a risk-oriented automated output.

Simulation Modeling.

For the numerical approbation of the proposed integral model of the influence of the human factor on the increase in the risk of the ergatic navigational support system, six scenarios were formed, reflecting typical and practically probable vessel operating modes: daytime passage in the open sea, coastal approach, crossing of a traffic separation scheme, night pilotage in confined waters, movement under restricted visibility conditions, and a storm emergency-strained mode in a narrow channel. Such a set of scenarios ensures a stepwise increase in information load, maneuvering complexity, the level of external disturbances, and the navigator's responsibility, thereby creating the necessary conditions for verifying the adequacy of the integral indicator over a wide range of functional states of the system.

Within each scenario, time series of parameters characterizing the internal state of the navigator, external disturbances, and control conditions were specified, in particular the coordinate of the center of gravity of the human factor $z_h(t)$, the external disturbing influence $M_{ext}(t)$, the moment of required corrections $M_{dem}(t)$, the angular characteristic $\theta^*(t)$, as well as the partial factors $E(t)$, $C(t)$, and $U(t)$. In addition, raw arrays of episodic, cognitive-temporal, and control-risk data were formed for each scenario, which made it possible to implement the calculation of the integral indicator in accordance with the structure of the model rather than on the basis of external simplified approximations.

Table 1 records the initial configuration of the simulation and defines the physical and operational context of the subsequent analysis. Its content shows that the scenarios were constructed according to the logic of sequentially increasing complexity: from the open sea with a low load to storm motion in a narrow channel with a critical level of uncertainty and a high frequency of forced corrections. It is precisely such a construction that makes it possible to interpret the results not as abstract mathematical values, but as estimates for real navigational situations.

The numerical approbation of the integral indicator was carried out by the Monte Carlo method, which made it possible to take into account parametric and scenario uncertainty.

Table 1 – Initial scenario parameters of the simulation modeling of the influence of the human factor on the increase in the risk of the ergatic navigational support system

scenario	***risk_level***	***navigation_situation***	***captain_interpretation***
S1_open_sea_day	low	Open sea day passage, good visibility, low traffic, normal watch conditions	Stable operating mode with minimal cognitive load
S2_coastal_approach	moderate	Coastal approach, more navigation objects, moderate traffic load	Growing information load and need for tighter monitoring
S3_tss_crossing	moderate_high	Traffic separation scheme crossing, dense crossing traffic	Tense watch condition with high decision responsibility
S4_pilotage_night	high	Night pilotage in narrow fairway / confined waters	Attention deficit risk and high pilotage responsibility
S5_restricted_ visibility	very_high	Restricted visibility in traffic area, uncertainty sharply increased	High uncertainty, strong temporal and cognitive strain
S6_storm_channel_ emergency	critical	Storm approach in narrow channel, emergency-like regime	Critical regime close to systemic stability loss

At each run, the weighting coefficients of the partial factors, the interaction parameters in the integral model, as well as the key input variables associated with the human factor and the external operating conditions of the system were varied. As a result, for each scenario, the mean value of the integral indicator $I_{HF \to R}$, its quantile bounds, and the probabilities of transition of the system to stable, strained, and critical modes were obtained.

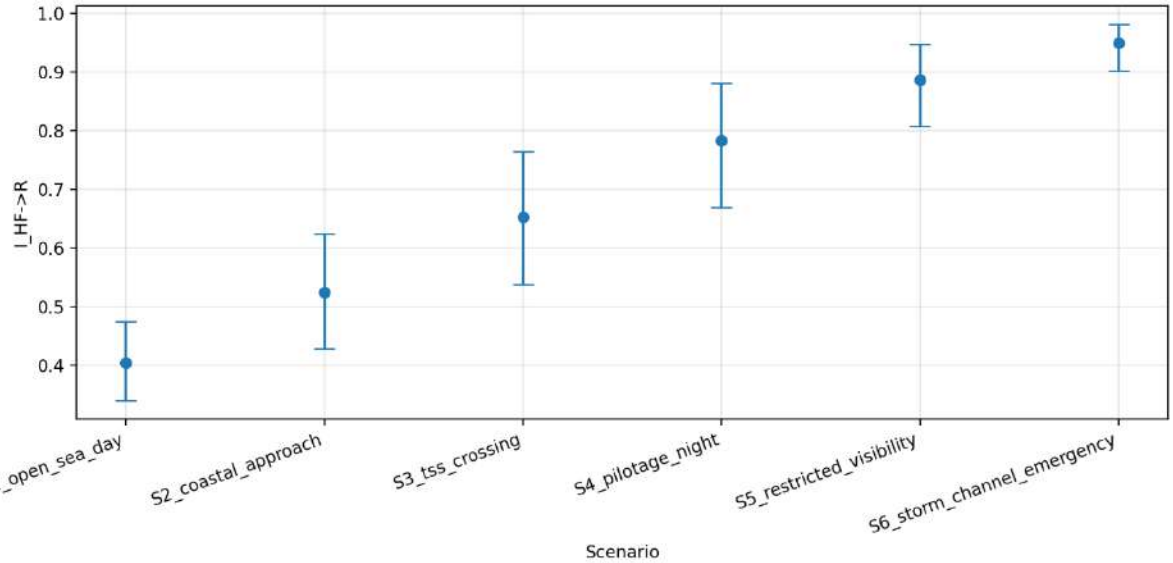

Figure 1 – Mean values of the integral indicator of the influence of the human factor on the increase in the risk of the ergatic navigational support system by scenarios with quantile bounds $Q_{0.05}$–$Q_{0.95}$

Figure 1 reflects the main integral result of the simulation. It shows a clear monotonic increase in the mean value of $I_{HF \to R}$ from the first to the sixth scenario. For the scenario S1_open_sea_day, the mean value of the integral indicator is about 0.404; for S2_coastal_approach, 0.524; for S3_tss_crossing, 0.652; for S4_pilotage_night, 0.783; for S5_restricted_visibility, 0.887; and for S6_storm_channel_emergency, 0.950. Such a pattern indicates the high sensitivity of the indicator to the complication of the navigational situation and confirms that the integral model adequately reflects the growth of the risk-generating influence of the human factor. At the same time, the quantile bounds demonstrate that, even taking Monte Carlo variability into account, the correct ordering of scenarios by risk level is preserved.

Table 2 – Generalized results of Monte Carlo modeling of the integral indicator $I_{HF \to R}$ by navigational situation scenarios

scenario	*I_mean*	*I_std*	*I_q05*	*I_q50*	*I_q95*
S1_open_sea_day	0.40426	0.041426	0.340121	0.402722	0.474752
S2_coastal_approach	0.523952	0.061069	0.428373	0.522832	0.62475
S3_tss_crossing	0.652503	0.070849	0.537867	0.653576	0.763895
S4_pilotage_night	0.783486	0.067119	0.669478	0.788845	0.881601
S5_restricted_visibility	0.886972	0.044208	0.807186	0.89319	0.947613
S6_storm_channel_emergency	0.949974	0.025061	0.902474	0.955075	0.981304

Table 2 numerically confirms the conclusions drawn from Figure 1 and makes it possible to assess the limits of variability more precisely. In particular, for the first scenario, the quantile interval is approximately 0.339–0.474, whereas for the sixth it is 0.902–0.981. This means that, as the scenario risk increases, not only does the mean value of the integral indicator increase, but the entire domain of its probable realizations is also shifted toward critical values. This property is important for the practical use of the model, since it makes it possible to interpret it not only in terms of mean estimates, but also in terms of confidence bounds of the risk state.

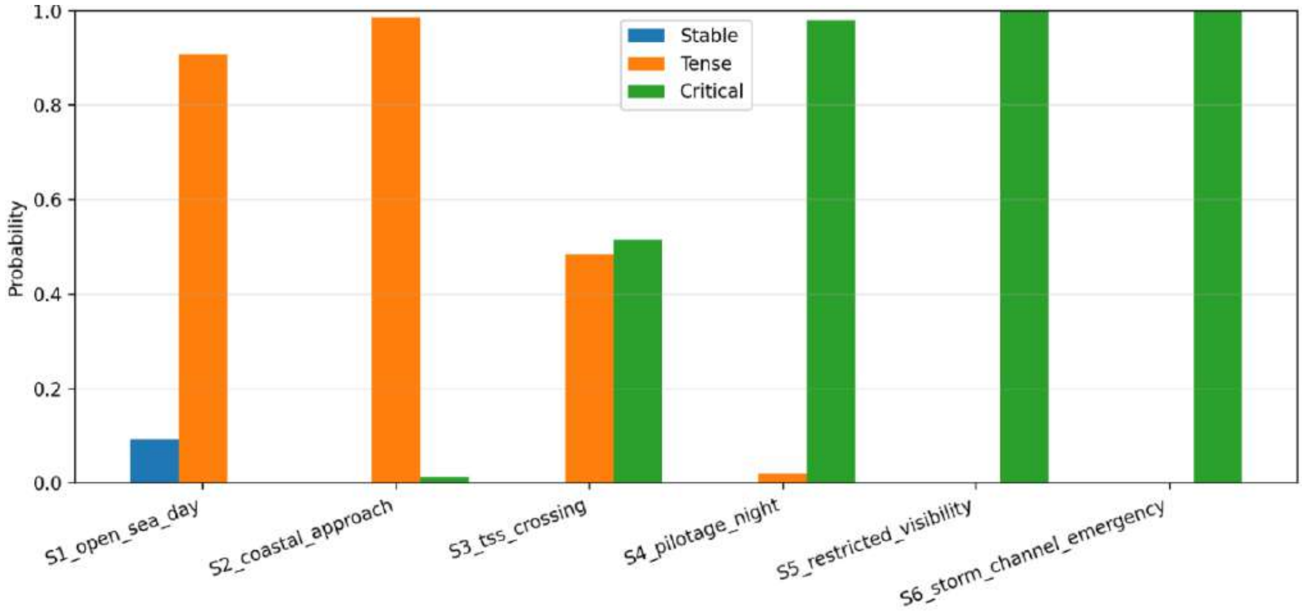

Figure 2 – Probabilities of the ergatic navigational support system being in stable, strained, and critical operating modes according to the results of Monte Carlo modeling

Figure 2 demonstrates the regime interpretation of the integral indicator. For S1_open_sea_day, the strained mode dominates with a small proportion of the stable mode, whereas the critical mode is practically not realized. For S2_coastal_approach, the strained mode remains predominant, but a small proportion of critical realizations appears. In the scenario S3_tss_crossing, the system enters a transitional region in which the strained and critical modes have close probabilities. Beginning with the scenario S4_pilotage_night, the critical mode already becomes almost completely dominant, while for S5_restricted_visibility and S6_storm_channel_emergency it effectively reaches unit probability. Thus, the integral indicator is suitable not only for quantitative assessment, but also for the classification of system operating modes and for identifying the threshold of transition to a dangerous state.

It is substantively important that the transition to the critical mode is observed not abruptly, but through an intermediate strained state, which corresponds to the real logic of navigation. This confirms the correctness of the regime scale of the model and its suitability for scenario forecasting.

Table 3 – Mean values of the partial factors $E(t)$, $C(t)$, $S(t)$, $U(t)$ and the dynamic stability parameters by scenarios

scenario	***E_mean***	***C_mean***	***S_mean***	***U_mean***	***mu_st_ mean***	***L_eff_ mean***	***Omega_ mean***	***R_ dynamic mean***
S1_open_sea_day	0.163	0.132	0.134	0.112	0.811	0.780	0.250	0.150
S2_coastal_approach	0.265	0.226	0.249	0.209	0.703	0.741	0.297	0.245
S3_tss_crossing	0.383	0.328	0.369	0.305	0.595	0.704	0.356	0.340
S4_pilotage_night	0.522	0.459	0.500	0.426	0.482	0.665	0.426	0.460
S5_restricted_visibility	0.688	0.598	0.638	0.565	0.370	0.628	0.507	0.600
S6_storm_channel_emergency	0.835	0.748	0.798	0.744	0.253	0.590	0.621	0.770

Table 3 performs the function of the internal decomposition of the integral indicator. It shows that, when moving from the first to the sixth scenario, not only the integral estimates increase, but also all the main partial components. In particular, the mean value of the episodic factor increases from approximately 0.163 to 0.835, the cognitive-temporal factor from 0.132 to 0.748, the dynamic-stability factor from 0.134 to 0.798, and the control-risk factor from 0.112 to 0.744. Thus, the increase in the integral indicator is formed not by a single local mechanism, but as a result of a coordinated deterioration of the behavioral, cognitive, dynamic, and control contours.

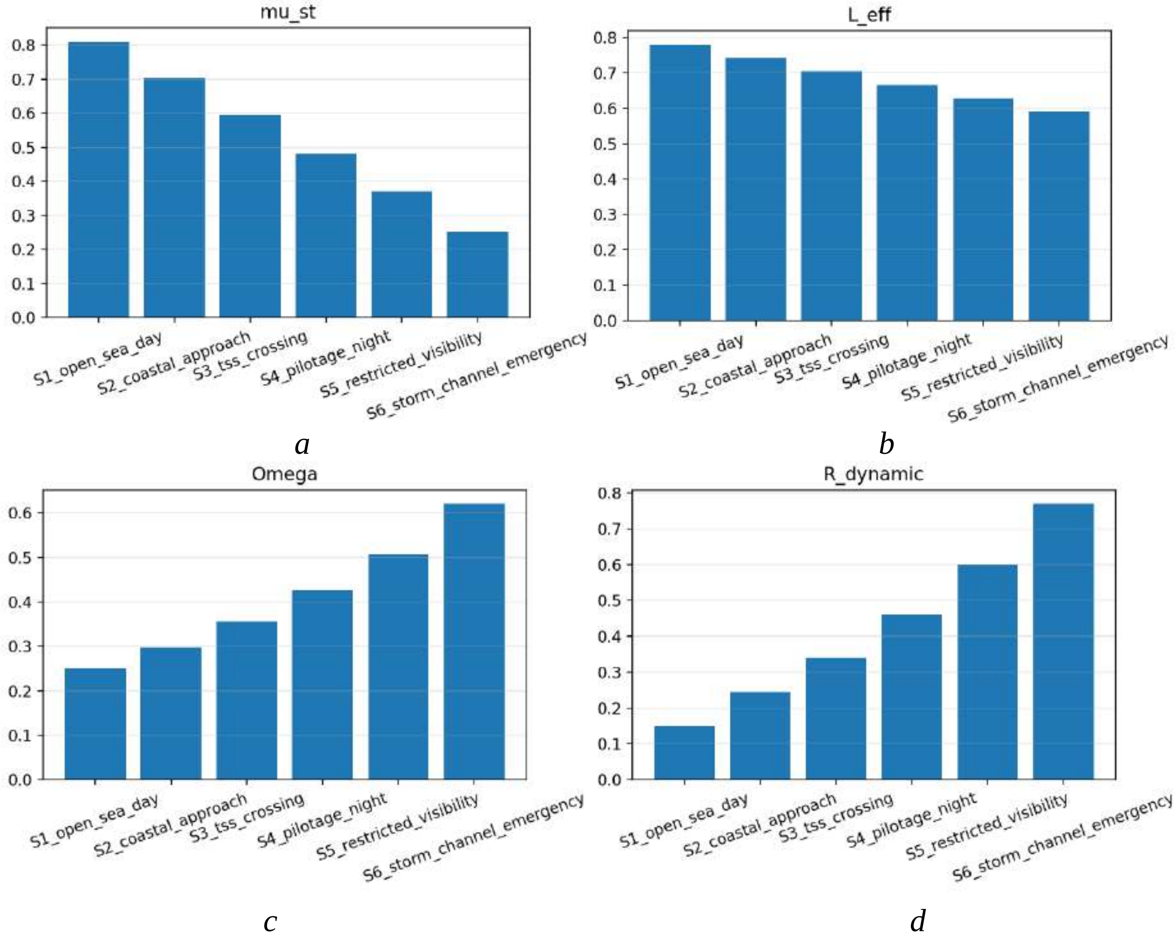

Figure 3 – Change in the mean values of the relative stability margin μ_{st} (*a*), effective functional reserve L_{eff} (*b*), forced correction frequency Ω (*c*), and dynamic risk $R_{dynamic}$ (*d*) across navigation scenario conditions

Figures 3a–3d confirm the consistency of the integral model with the basic dynamic apparatus. Figure 3a shows a successive decrease in the relative stability margin μ_{st} from 0.811 for S1_open_sea_day to 0.253 for S6_storm_channel_emergency. This means that, with the increasing influence of the human factor, the system loses the ability to maintain a stable mode without intensifying corrective actions.

Figure 3b demonstrates an analogous decrease in the effective functioning reserve L_{eff} from approximately 0.780 to 0.590. This indicates a degradation of the functional resource of the system and confirms that the human factor in the model acts not as an external commentary, but as an internal parameter that changes the real characteristics of the dynamics.

Figure 3c shows an increase in the frequency of forced corrections Ω from 0.250 to 0.620. Thus, as the scenario deteriorates, the system is forced to compensate for the loss of stability increasingly often by active control actions. Finally, Figure 3d shows an increase in the dynamic risk $R_{dynamic}$ from 0.150 to 0.770, that is, from a low-risk to a distinctly critical level. Taken together, these four figures prove that the integral indicator $I_{HF \to R}$ is consistent with the dynamic nature of the system and reflects the real mechanism of transition from a stable to a risky mode.

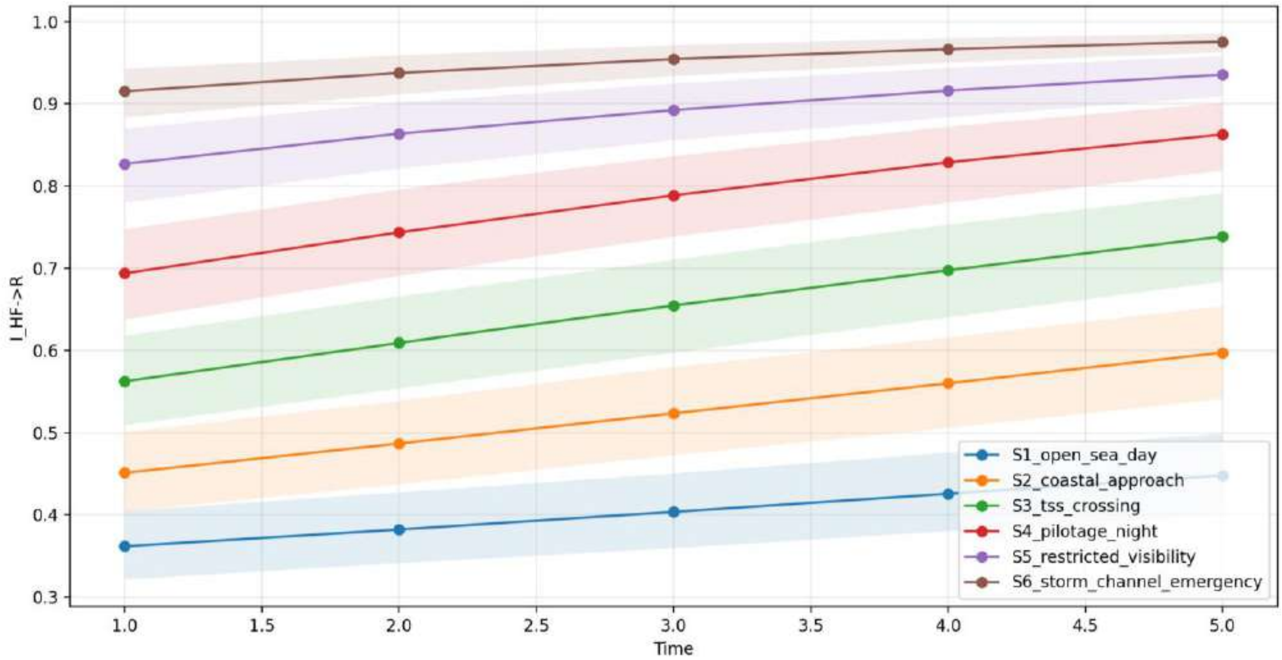

Figure 4 – Temporal evolution of the integral indicator $I_{HF\to R}$ in six operating scenarios of the ergatic navigational support system

Figure 4 shows that the integral indicator changes regularly not only between scenarios, but also over time within each scenario. For low-risk scenarios, the growth of $I_{HF\to R}$ is moderate, whereas for high-risk and critical scenarios the curves are steeper. This means that the model is suitable not only for the static comparison of operating conditions, but also for quasi-real-time monitoring of situation development. It is precisely this property that is fundamentally important for decision-support systems, in which it is necessary not merely to record an already formed dangerous state, but to track the trajectory of its approach in advance.

Table 4 – Probabilities of transition of the ergatic system to stable, strained, and critical operating modes

scenario	*P_stable*	*P_tense*	*P_critical*
S1_open_sea_day	0.0916	0.9084	0
S2_coastal_approach	0	0.986933	0.013067
S3_tss_crossing	0	0.485	0.515
S4_pilotage_night	0	0.0196	0.9804
S5_restricted_visibility	0	0	1
S6_storm_channel_emergency	0	0	1

Table 4 is a numerical complement to Figure 2 and makes it possible to trace the change in the regime structure of the system in detail. It shows that, for the first scenario, the share of the stable mode is about 0.092, the strained mode 0.908, and the critical mode is practically absent. For the second scenario, the share of the critical mode is already approximately 0.013; for the third, 0.516; for the fourth, 0.979; and for the fifth and sixth, it reaches unity. Thus, the model provides a clear quantitative representation of the transition of the system from predominantly strained to critical functioning.

Table 5 – Results of the sensitivity analysis of the integral indicator $I_{HF \to R}$ to variations in the main model parameters

variable	***spearman_rank_corr***
E	0.988951957
$R_{dynamic}$	0.98870102
U	0.988598384
C	0.988598384
S	0.985383299
z_h	0.982032815
μ_{st}	0.982032815
L_{eff}	0.982032815
Ω	0.956732892
θ_E	0.051237313
θ_C	0.046449323
θ_S	0.040946005
θ_U	0.038674436

Table 5 demonstrates the results of the sensitivity analysis and is an important argument in favor of the internal mathematical consistency of the model. The greatest contribution to the formation of the integral indicator is made by the episodic factor E ($\rho \approx 0.989$), the dynamic risk $R_{dynamic}$ ($\rho \approx 0.989$), the cognitive-temporal factor C ($\rho \approx 0.988$), the control-risk factor U ($\rho \approx 0.988$), and the dynamic-stability factor S ($\rho \approx 0.986$). A high influence is also exerted by the coordinate of the center of gravity of the human factor z_h, the stability margin μ_{st}, the effective reserve L_{eff}, and the frequency of forced corrections Ω. At the same time, random variations of the individual weighting coefficients θ_E, θ_C, θ_S, θ_U have a significantly smaller local contribution, which confirms the dominance of the substantive physical-behavioral components of the model over the technical calibration parameters. Its analysis confirms that the integral indicator is most sensitive precisely to those factors that were theoretically laid at the foundation of the model: behavioral, cognitive-temporal, dynamic-stability, and control-risk. This means that the model contains no internal logical contradiction and responds to changes in key parameters in accordance with its mathematical structure.

Thus, the set of results presented in Tables 1–5 and Figures 1–4 confirms the adequacy of the proposed integral model. First, a monotonic increase in the integral indicator is observed with increasing scenario risk. Second, this tendency is consistent with a decrease in the stability margin and functioning reserve, as well as with an increase in the frequency of forced corrections and dynamic risk. Third, the probabilistic interpretation of the results demonstrates a regular transition of the system from stable and strained modes to the critical mode. Finally, the sensitivity analysis shows that the integral indicator is determined precisely by the basic substantive factors of the model. Taken together, this gives grounds to consider the proposed approach suitable for the quantitative assessment of the influence of the human factor on the increase in the risk of the ergatic navigational support system and for further application in decision-support systems and adaptive automated control.

Conclusions

1. A generalized model for controlling ergatic systems and means of navigational support has been developed, in which the navigator, the vessel, the navigational-information environment, and the regulatory-situational constraints are considered as elements of a unified functional space.

2. It has been shown that the transition from raw AIS/ECDIS data to the standardized series constitutes an independent methodological level of the model, at which a unified temporal-spatial analytical space is formed, suitable for the mathematical interpretation of motion microdynamics.

3. A fractal-episodic approach to the identification of local vessel micromotions has been substantiated, within which episodes are encoded by the fractal code *FC-abcdef*, combined with the quantitative assessment of episodic risk, and form a formalized behavioral-risk space of the navigator's actions.

4. Models of attention distribution, temporal states, subjective time distortion, and p-adic complexity of the situation have been integrated into a unified cognitive-temporal block, which makes it possible to formalize the internal states of the navigator as variables of the ergatic system.

5. A gravitational-inertial interpretation of the human factor has been formed through the coordinate of the center of gravity $z_h(t)$, the effective stiffness $k_{eff}(t)$, the stability margin $\mu_{st}(t)$, the frequency of forced corrections $\Omega(t)$, and the integral risk $R(t)$, which provides a formal mechanism for the transition from the navigator's state to the dynamics of stability of the ergatic system.

6. The applied output of the generalized model into risk-oriented and automated control contours has been demonstrated, namely: p-adic structuring of the situation, multicriteria risk functionals, domains of admissible control actions, automated multi-target collision avoidance, and the formation of safe storm navigation modes.

7. An integral indicator of the influence of the human factor on the increase in the risk of the ergatic navigational support system has been developed, which, in logistic-normalized form, combines episodic behavioral, cognitive-temporal, dynamic-stability, and control-risk components. This made it possible to move from the isolated analysis of individual manifestations of the navigator's activity to a unified quantitative assessment of the total risk-generating influence of the human factor on the functioning of the navigational contour.

8. It has been shown that the numerical approbation of the integral indicator by the Monte Carlo method provides the possibility of calibrating model parameters, assessing the variability and robustness of results, determining the probability of the system's transition to stable, strained, and critical modes, as well as ranking dominant risk factors by means of global sensitivity analysis. This creates the basis for using the proposed approach in decision-support systems and the automated control of human-factor risks in navigation.

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Носов П. С. УЗАГАЛЬНЕНА МОДЕЛЬ УПРАВЛІННЯ ЕРГАТИЧНИМИ СИСТЕМАМИ НАВІГАЦІЙНОГО ЗАБЕЗПЕЧЕННЯ З ІНТЕГРАЛЬНИМ ПОКАЗНИКОМ ВПЛИВУ ЛЮДСЬКОГО ФАКТОРА

У статті розв’язано актуальне наукове завдання розроблення узагальненої моделі управління ергатичними системами навігаційного забезпечення з інтегральним показником впливу людського фактора судноводія на підвищення ризику функціонування системи. Запропонований підхід ґрунтується на визначенні дій судноводія не як зовнішнього джерела випадкових похибок, а як внутрішнього параметра ергатичної системи, що визначає якість сприйняття навігаційної ситуації, своєчасність реакцій, характер керувальних дій і рівень безпеки руху судна. Метою роботи є побудова інтегрованої моделі, яка поєднує системне подання ергатичної системи, формалізацію AIS/ECDIS-даних, фрактально-епізодне представлення мікрорухів судна, моделі когнітивно-часових і психофізіологічних станів судноводія, гравітаційно-інерціальну інтерпретацію стійкості та ризик-орієнтований контур керування. Наукова новизна полягає у введенні інтегрального показника, що в логістично-нормованій формі об’єднує епізодний поведінковий, когнітивно-часовий, динамічно-стійкісний і керувально-ризиковий компоненти в єдиний інформаційно-аналітичний контур. Для чисельної апробації моделі застосовано метод Монте-Карло, який забезпечує калібрування параметрів, оцінювання варіативності, робастності, чутливості та ймовірностей переходу системи до стійкого, напруженого і критичного режимів. Імітаційне моделювання для шести сценаріїв навігаційної ситуації підтвердило монотонне зростання інтегрального показника зі збільшенням сценарної складності, узгоджене зі зменшенням запасу стійкості та резерву функціонування, а також зі зростанням частоти вимушених корекцій і динамічного ризику. Практичне значення роботи полягає у можливості використання запропонованої моделі в системах підтримки прийняття рішень, моніторингу стану судноводія та адаптивного автоматизованого керування безпечними режимами руху судна.

Ключові слова: *ергатична система; навігаційне забезпечення; людський фактор; безпека мореплавства; судноводій; AIS/ECDIS-дані; фрактально-епізодний аналіз; інтегральний показник ризику; автоматизоване керування рухом.*

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