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A Methodology to Evaluate the Effectiveness of Intelligent Ship Navigational Information Monitoring System

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ABSTRACT The perception and acquisition of navigation-related information are essential for the safety of intelligent ship. To address the effectiveness of navigational information monitoring system designed for the intelligent ship, in the present study, a comprehensive evaluation methodology is proposed. The various functions designed for obtaining corresponding navigational information are re-organized to develop the structure of intelligent ship navigational information monitoring system, which is subjected to evaluate the effectiveness by analyzing the information behavior processes in this proposed system and the available information monitoring technologies applied on intelligent ships. The orthogonal exploratory analysis technique was applied to establish the functional relationship between system effectiveness and contributing subsystems, as a result, the contribution degree distribution of contributing subsystems identified for system effectiveness is obtained. Finally, an application of the proposed methodology verifies its feasibility in calculating system effectiveness and its potential to extend to intelligent ships at different levels. The present study provides a new perspective to understand the safety of intelligent ships, and the comprehensive evaluation methodology provides a new path for the effectiveness analysis of intelligent ship navigational information monitoring system.

INDEX TERMS Intelligent ship, navigational information monitoring, system effectiveness, exploratory analysis, orthogonal test.

I. INTRODUCTION

Driven by artificial intelligence (AI) technology and the demand of the shipping market, 'intelligent' ships have become the focus of future ship development [1]. The deployment of unmanned, autonomously operable, internet-connected, integrated ships controlled by AI algorithms is dependent on accurate navigational information, and the requirements for their monitoring capabilities are continually increasing. Similarly, with the development of human society and the progress of science and technology, things or systems achieve specific mission goals through interconnection, interaction and coordination, showing the characteristics of intensive, efficient and emerging. The interactivity and complexity between these systems make the safety issues associated with intelligent ships as the main concern for shipping industry, as a result, some artificial intelligence technologies, such as Bayesian network, artificial neural network [2], are applied to improve the safety level of shipping operations. Actually, navigational information monitoring system is the integration of interdependent components, which are related and linked to provide a defined capability requirement. Removing any components that makes up the system will greatly affect the overall effectiveness or capability of the system [3]. The intelligent development of the ship has interconnected the traditional divided information system and produced the overall efficiency. Therefore, ensuring the effectiveness of intelligent ship navigational information system (ISNIMS) is particularly important for the safe navigation of intelligent ships. The primary basis for improving the effectiveness of ISNIMS and guaranteeing its stability is the scientific analysis of its composition and

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how it is distributed. However, with the widespread application of advanced information sensing technology and AI in shipping industry, the navigational information monitoring system has become more intelligent, but its internal composition architecture and interactions have also become more complex and uncertain. Therefore, how to accurately evaluate the uncertain relationships between the internal components and the effectiveness of this monitoring system has become the key problem to ensure the navigation safety of intelligent ships.

Because of extensive global research on designing and manufacturing intelligent ships, a large number of reports on intelligent ship navigational information monitoring have recently emerged. At present, the related research on navigational information monitoring mainly focused on the intelligent perception and intelligent integration of navigational information, with less investigation into the system effectiveness and its contribution. System effectiveness refers to the expected degree that the system can accomplish a specific task., and it is an important evaluation index to represent the system to complete the assigned task. By studying the effectiveness status and contribution distribution of ISMOS system, the actual operation condition of the system can be accurately grasped. In practice, ‘fuzzy’ comprehensive evaluations and Bayesian networks were mainly used to analyze the performance indices related to the navigational information monitoring system of intelligent ships [4]–[7]. The fuzzy comprehensive evaluation method has been successfully applied to intelligent decision-making, system performance, collision avoidance, and navigation safety [8]–[10]. However, this method is greatly affected by the subjectivity of the scorer, and it lacks objectivity in the analysis of the navigational information monitoring system designed for intelligent ships. Similarly, the Bayesian network analysis method has been applied successfully in the areas of intelligent navigation control, continuous optimization of intelligent navigation, and intelligent information fusion. However, this method relies more on regression analysis of prior experience in evaluating the internal networks, and it lacks applicability for the analysis of the relationship between discontinuous complex systems [11]–[14]. In practice, many studies have used testing methods to analyze the effectiveness of navigational information monitoring, such as an testing statistical classification algorithm to analyze the internal relevance of an intelligent ship’s decision-making system or simulation to analyze the impact of intelligent ship navigational information on collision avoidance [15], [16]. In a recent report, it was proposed to apply exploratory methods to analyze the effectiveness of complex system by analyzing the relationship between system composition and system operation efficiency [17], [18]. However, this method used influence factor traversal, resulting in a large number of samples, and it was highly dependent on sophisticated computer simulations. For system analysis which cannot be directly simulated by computer, there are limitations in test cost and test times.

In this study, by analyzing the basic functions and information behavior processes of the navigational information monitoring system designed for intelligent ships, we proposed an exploratory analysis methodology based on orthogonal test. With reference to the development path of intelligent ship technology, the methodology established the interactive relationship and ability level division standard for the information monitoring system designed for intelligent ships, and the use of orthogonal test reduced the number of tests. The test results were then measured under different combinations of factors, and the internal relationships and effectiveness contribution strengths between the subsystems and the system were analyzed.

II. FRAMEWORK OF THE NAVIGATIONAL INFORMATION MONITORING SYSTEM FOR INTELLIGENT SHIP

A. COMPOSITION

The main purpose of the ISNIMS is to intelligently perceive and fuse navigational information, then make intelligent decisions according to the corresponding ship navigation rules and tasks [19], [20]. After completion of the decision-making process, the necessary actions are executed to respond to changes in the navigation process by distributing the corresponding instructions [21]. Based on an analysis of the transfer characteristics of the intelligent navigational information, the system is divided into five main subsystems: the intelligent perception system (IPS), the intelligent fusion system (IFS), the intelligent decision-making system (IDMS), the intelligent distribution system (IDS), and the intelligent communication system (ICS), as shown in Figure 1.

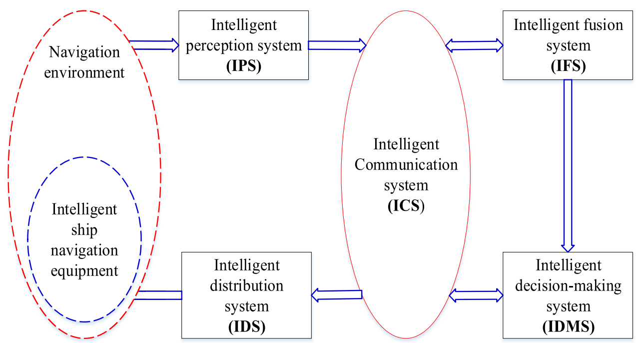

FIGURE 1. Diagram of navigational information monitoring system designed for intelligent ship.

The IPS is composed of various sensing equipment, sensing networks and information receiving equipment that collect the navigational information from the ship and the surrounding environment. In addition to safe and reliable hardware, the IPS also includes a suite of receiving software adapted to a variety of target information data formats [22], [23].

The IFS is mainly a process of filtering and fusing perceptual information according to certain standards, including data format conversion, track fusion, information data classification, marking and storage.

The IDMS mainly refers to the analysis and decision-making of the fusion information by using the corresponding AI algorithm and providing the necessary instructions, including optimization of the ship's route and speed, and the activation of automatic collision avoidance during the ship's rendezvous [24].

The IDS is mainly composed of information exchange equipment and security equipment that evaluates whether the instructions generated by the decision-making system are accurately sent to the designated response system.

The ICS mainly refers to wired and wireless channels and communication terminal equipment used to ensure the rapid and uninterrupted flow of information between interactive systems.

B. FUNCTION ANALYSIS

The navigational informational monitoring system receives the perceptual information from the IPS and the instructions from the remote center and the human intervention system, and performs information fusion, data cleaning, and data storage calls. The system then formulates intelligent navigation adjustment instructions through the IDMS, and finally issues the instructions to the relevant intelligent ship navigation equipment and remote equipment in accordance with regulations. The capabilities of the navigational information system must be sufficient for the following processes:

- Maximum perceived range. The perceived range of the onboard sensing system, space sensing equipment and shore-based monitoring center must meet the perception requirements.
- Information acceptance capability. The intelligent ship can receive navigational information transmitted by the sensing equipment on various associated channels. The remote centers and direct sensing equipment must meet the minimum quantity requirements.
- Information fusion capability. The information received by the IPS is processed by normalization, filtering, classification, etc. Under the given confidence level, the fusion process needs to achieve a certain rate, in order to effectively store and recall information.
- Information transmission capability. The navigational information monitoring system can use wired or wireless communication for data transmission for the specified communication distance. The data transmission must meet the required transmission success rate. The response time and command transmission time from receiving the target data to displaying the instructions must meet the usage requirements of the task.
- Information distribution capability. The navigational information monitoring system must be able to distribute the IDMS instructions to the corresponding intelligent ship navigation equipment according to the requirements, and the notification and distribution abilities must meet the minimum usage requirements.
- Multi-environment adaptability. The navigational information monitoring system can adapt to a complex and changeable navigation environment. The mean time between failures and the maintenance time of the system must meet the requirements of intelligent ship navigation, and the system must be able to keep information secure [25].

C. INFORMATION BEHAVIOR DESCRIPTION

Complete information monitoring depends on large numbers of information exchange processes [26]; therefore, describing information behavior is helpful for understanding the process characteristics of the monitoring system and can provide a reference for selecting the evaluation indicators. Through investigation and analysis, the information behavior correlative network of the navigational information monitoring system associated with intelligent ship was established as shown in Figure 2.

In the specific information behavior process, the various monitoring subsystems first individually report to the same level information-processing unit or directly to the IPS, bypassing the first level. These subsystems also report their working status to the IDMS and receive instructions from the IDMS or from the remote center. Each information processing unit receives the information reported by the monitoring equipment at the same level, performs information screening, and reports the processing results to the IPS. Based on this information flow, the monitoring range of the navigational information monitoring system can be determined for the time, space, and frequency domains and the type of monitoring target can be determined. Secondly, the IDMS receives the fused information reported by IFS, reports the working status information of the system itself to the remote center and receives command and control orders. Based on this information flow, the accuracy of the navigational information, whether adherence to information demands is satisfactory, and any abnormalities in information processing can be determined. Thirdly, the IDS receives the comprehensive information orders from the IDMS and distributes them to the information demand department and to the response system based on the navigational requirements. Through this information flow, the timeliness, bit error rate, and information transmission veracity of the navigational information monitoring system can be determined.

III. METHODOLOGY BASED ON EXPLORATORY ANALYSIS

Exploratory analysis is a methodology for measuring and evaluating uncertainty in high-level systems. It is proposed by the American Rand Corporation for evaluating the effectiveness of their equipment system [27]. It is mainly used for an overall study of the results corresponding to uncertainty factors, and it is a comprehensive, sensitive analytical methodology. The methodology is based on an understanding of the influential relationships among data variables associated with complex phenomena by examining a wide range of possible results of various schemes under a large number of uncertain conditions. Compared with traditional sensitivity

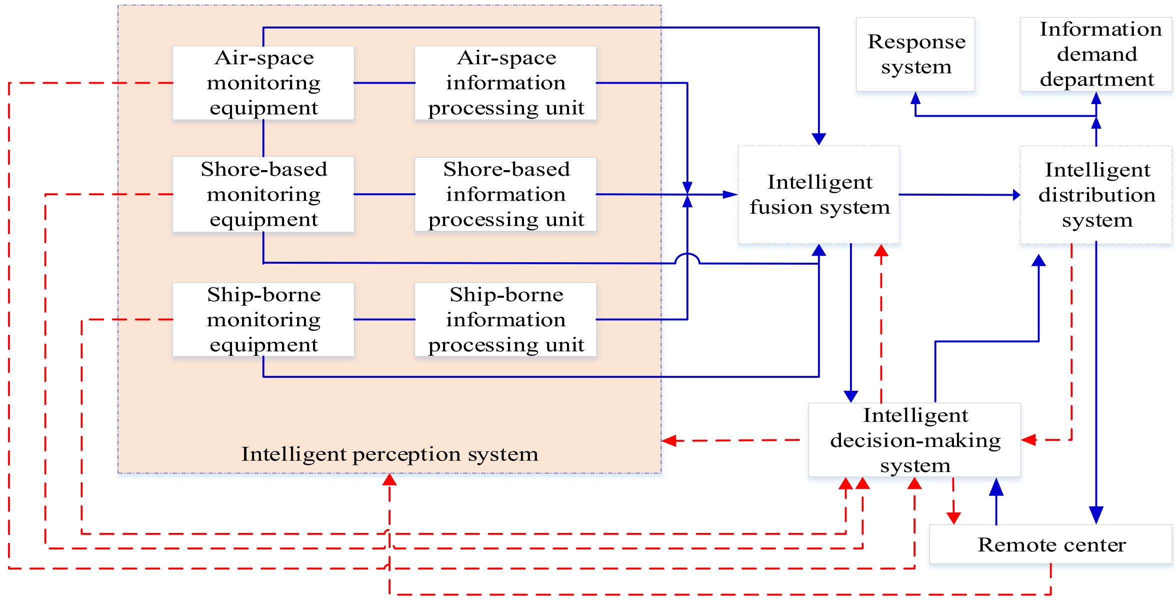

FIGURE 2. Information behavior correlative network involved in navigational information monitoring system.

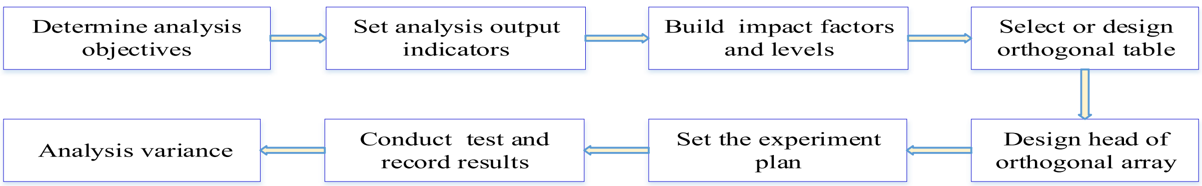

FIGURE 3. The orthogonal exploratory analysis process.

analysis methodology, exploratory analysis has the advantage of comprehensive coverage in dealing with uncertainty factors and avoids the limitations of small-scale changes under a theoretical optimal solution. By comprehensively testing the results of the problem under various combinations of factors and determining the inherent relationships between the uncertainty factors and the problem results, a robust solution to various uncertainty factors can be obtained. This methodology is especially suitable for the investigation of uncertainty in complex systems. Due to the uncertainty of the interactions, exploratory analysis cannot be effectively simulated by computer. Also, the ergodic test method is not feasible because the number of trials needed would require a huge investment in time and money. Therefore, we introduced an orthogonal test method to reduce the number of tests and improve the applicability of exploratory analysis on the premise of ensuring a positive effect on test analysis. Orthogonal test is a method used for multi-factor analysis. It selects some representative points from the comprehensive test and then analyzes the effects of different operating levels of each component system based on the test results [28]. From the results, it infers the overall capability of the system under the condition of any component system, any operation level matching, and the significance level of the influence of the component parts on the system goals. The basic steps are as shown in Figure 3.

A. ORTHOGONAL TEST DESIGN

In this study, the probability of completing the task of monitoring the navigational information was used to evaluate the operational effectiveness of the ISNIMS. Based on analysis of the subsystems and information system behavior processes, the five subsystems-intelligent perception, intelligent fusion, intelligent decision-making, intelligent communication, and intelligent distribution-were set as orthogonal exploratory factors. An effectiveness exploratory analysis structure of the proposed navigational information monitoring system was established as shown in Figure 4.

By combining the various operating levels of the five subsystems, different combinations were obtained. The influence of different operating levels of the subsystems in these combinations on the system effectiveness can be analyzed to obtain the contribution of the subsystems to the system effectiveness, and consequently the monitoring ability of the navigational information monitoring system composed of different operation levels can be predicted and analyzed. In terms of parameter setting, according to the actual technical level of the intelligent ship equipment and the three-level

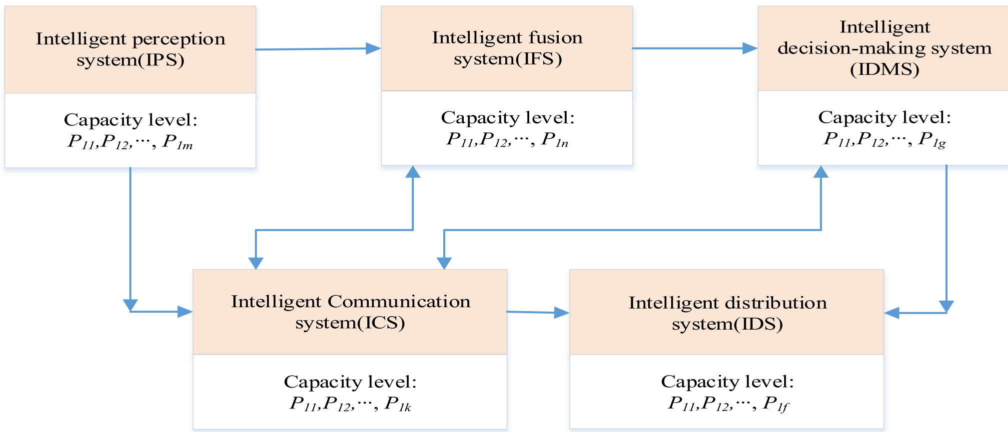

FIGURE 4. System effectiveness exploratory analysis structure.

classification standards for intelligent ship design, we assumed that each subsystem had three different operating levels by the reference standards for the capability setting of each subsystem corresponded to the classification standards of the interconnection, remote control, and autonomous navigation of intelligent ships [29]. So that, the probability of completing the set task appeared as high, medium or low, which were shown in Table 1. The subsystems with different operating levels form 35 combinations. Through statistical analysis, the numerical relationship between subsystem operating level and task completion was determined and an exploratory analysis of the system effectiveness was formulated.

TABLE 1. Operating level of the subsystems.

Level	IPS(A)	IFS(B)	ICS(C)	IDMS(D)	IDS(E)
1	P_{1low}	P_{2low}	P_{3low}	P_{4low}	P_{5low}
2	P_{1mid}	P_{2mid}	P_{3mid}	P_{4mid}	P_{5mid}
3	P_{1high}	P_{2high}	P_{3high}	P_{4high}	P_{5high}

As ICS was the material basis for the information transmission in IPS, IDMS, and IDS, the interactions among the constituent systems were considered in the exploratory analysis. For the single and non-linear of the equipment performance, the conventional method is to conduct 11^3 tests on all combinations, but it is not allowed in time and economic conditions.

In addition, considering the subsequent orthogonal test analysis of variance, it was necessary to ensure that the orthogonal table had an empty error column. So, an orthogonal table and its corresponding interaction list were used to construct the orthogonal headers, which was shown in Table 2.

In Table 2, the level values in the interaction column were only used for statistical analysis and had no effect on the arrangement of the test. The arrangement of test conditions was the same as that without considering the interaction, and only the horizontal combination in the column of influencing factors was arranged for the test.

TABLE 2. Orthogonal headers under interactive relationships.

No.	1	2	3	4	5	6	7
Subsystem	C	A	$(C\times A)_1$	$(C\times A)_2$	E	$(C\times E)_1$	$(C\times E)_2$
No.	8	9	10	11	12	13	
Subsystem	D	$(C\times D)_1$	$(C\times D)_2$	error	B	error	

B. DATA ACQUISITION

Based on the above analysis of the navigational information behavior characteristics, it is found that the operating ISNIMS involves the physical domain, the information domain, and the cognitive domain simultaneously.

The physical domain of navigational monitoring is the area in which information monitoring interacts with shore-based, space-based and other monitoring equipment, and it is also the area that supports the information transmission and communication network [30]. The information domain of navigation monitoring is the space that implements the capture, identification and fusion of information in ISNIMS as well as the generation, processing and sharing of information. The cognitive domain of navigation monitoring is the area in which the navigational information monitoring command center assigns and performs monitoring tasks.

This multisystem indicate monitoring process handles the information that is the main carrier of interaction behaviors that traverse the three domains; maintaining the validity of the information is the key to ensuring the ISNIMS operating effectively. Based on the characteristics of information integrity, accuracy and timeliness, the ISNIMS effectiveness evaluation indicators framework is designed to accurately represent the effectiveness of the various underlying

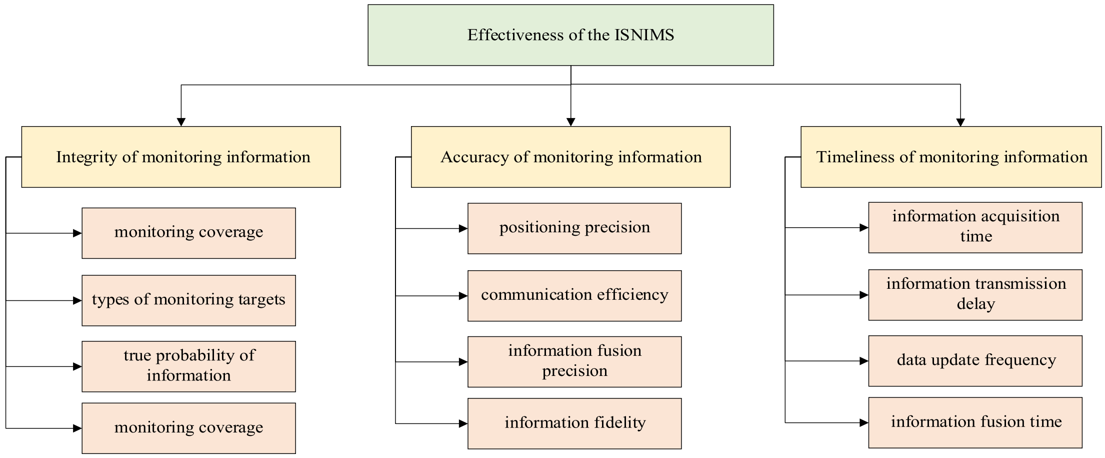

FIGURE 5. ISNIMS effectiveness evaluation indicators framework.

subsystems [31]. As shown in Figure 5, 12 key indicators representing information integrity, accuracy and timeliness were selected.

A comprehensive measurement can be applied to calculate the effectiveness of ISNIMS as follows:

$$E_{recon} = f_{recon}\left(E^1_{recon}, E^2_{recon}, E^3_{recon}, \omega_1, \omega_2, \omega_3\right) \quad (1)$$

where $f_{recon}(\cdot)$ is an aggregation function that represents ISNIMS effectiveness, E^1_{recon} represents the integrity of monitoring information, E^2_{recon} represents the accuracy of monitored information, E^3_{recon} represents the timeliness of monitoring information, and ω_1, ω_2, and ω_3 indicate the relative importance of the three indicators.

1) INTEGRITY

The integrity of monitoring information mainly refers to the completeness of the information provided by ISNIMS, which as measured by four indicators: monitoring coverage, types of monitoring targets, true probability of information and probability of information fusion. To facilitate an equal weight calculation of information data, the dimensionless processing method of 'initial value' is adopted in data unification [32]. Among them, monitoring coverage is the main indicator used to measure the operational efficiency of the monitoring system. The ISNIMS is required to have a large monitoring coverage that allows discover interference to navigation information as far as possible and as early as possible. The types of monitoring information are utilized to reflect the completeness of the navigational information that ISNIMS monitors. The factual information monitoring probability is used to reflect the completeness of the monitoring system for a ship's navigation state. The probability of information fusion is used to reflect the ability to fuse multisensory information fusion in the navigational monitoring system. The integrity of navigational monitoring information refers to the proportion of the number of navigational information items monitored, identified and fused by the monitoring system within its maximum coverage, which can be expressed by the numerical probability $P_{recon}\left(I_{completeness}\right)$; therefore, we can obtain $E^1_{recon} = P_{recon}\left(I_{completeness}\right)$.

The front and back boundary of ISNIMS is expressed as α_f and α_b, and the detection distance of ISNIMS is expressed as d. Assuming that the monitoring targets are evenly distributed in 360 degree space, and the theoretical detection distance required by the task is set as H, the maximum coverage probability P_{11} can be calculated as follows:

$$P_{11} = \frac{\left|\alpha_b - \alpha_f\right|}{360} \times \frac{d}{H} \quad (2)$$

Based on the above descriptions in Figure 1 and Figure 2, it is found that the ISNIMS mainly has five types of information sources: image information, signal information, measurement and characteristic information, intelligent information, and open source information, as shown in Figure 6.

Assuming that the number of information types needed for safe navigation of the ship is N_1 and the number of real information types monitored by the ISNIMS is n_1, the monitoring probability of the ISNIMS for the information types P_{12} is defined as follows:

$$P_{12} = \frac{n_1}{N_1} \quad (3)$$

Similarly, assuming that the quantity of information needed for safe navigation of the ship is N_2 and the quantity of real information monitored by the ISNIMS is n_2, the monitoring probability of the ISNIMS for the information quantity P_{13} is defined as follows:

$$P_{13} = \frac{n_2}{N_2} \quad (4)$$

Also, assuming that the quantity of real information by multi-sensor information fusion processing system is n_3, the information fusion probability of the ISNIMS P_{14} is

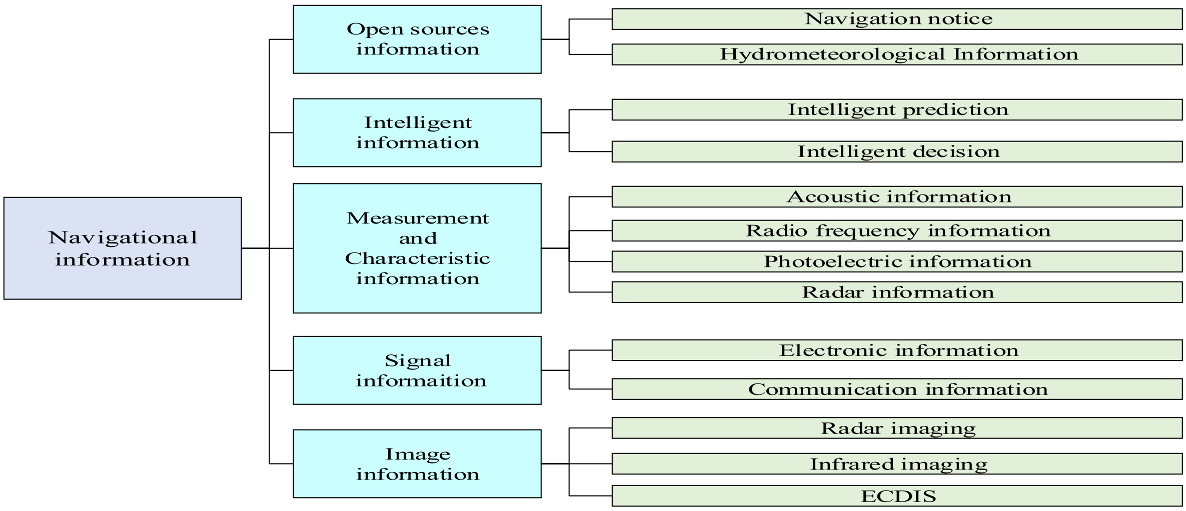

FIGURE 6. **Types of navigational information.**

defined as follows:

$$P_{14} = \frac{n_3}{n_2} \tag{5}$$

Therefore, the information integrity of the ISNIMS can be defined as follows:

$$\begin{aligned} E^1_{recon} &= P_{recon}\left(I_{completeness}\right) \\ &= f^1_{recon}\left(P_{11}, P_{12}, P_{13}, P_{14}; \omega_{11}, \omega_{12}, \omega_{13}, \omega_{14}\right) \end{aligned} \tag{6}$$

where $f^1_{recon}(\cdot)$ represents an aggregation function for the information integrity, and $\omega_{11}, \omega_{12}, \omega_{13}$, and ω_{14} indicate the relative importance of the four indicators.

2) ACCURACY

The accuracy of monitoring information refers to the ability to accurately monitor, acquire and identify the objective navigational information. This concept can also be expressed as the degree of agreement between the acquired information and the real information, including positioning precision, communication efficiency, information fusion precision, and information fidelity. This degree can be calculated by the numerical probability $P_{recon}\left(I_{correcteness}\right)$; thus, we can obtain $E^2_{recon} = P_{recon}\left(I_{correcteness}\right)$.

a: POSITIONING PRECISION

Positioning precision mainly represents the error between the real values and values measured by radar, satellite, telex and other devices. Assume that the offset error of the ship's safe navigational requirement is α, and the average deviation between the information value measured and the true information value is $\bar{\mu}$. If $\bar{\mu} < \alpha$, then the position precision $P_{21} = 1$; otherwise, $P_{21} = \alpha/\bar{\mu}$.

b: COMMUNICATION EFFICIENCY

The communication efficiency of the ISNIMS refers to the weighted average of the efficiency of voice communication, message transmission, and image transmission. Among these, voice communication efficiency p_1 is defined as the ratio of acceptable voice communications to the total number of voice communications. The efficiency of message transmission p_2 refers to the ratio of the number of successfully sent or received texts to the total number of texting attempts. The efficiency of image transmission p_3 is defined as the ratio of the number of successful image communications to the total number of attempted image communications. Applying the weighted average algorithm, the communication efficiency of the ISNIMS P_{22} can be calculated as follows:

$$P_{22} = p_1 a_1 + p_2 a_2 + p_3 a_3 \tag{7}$$

where a_1, a_2, and a_3 indicate the relative importance of the three indicators.

c: INFORMATION FUSION PRECISION

The precision of information fusion refers to the error between the measured values of information and the actual values after information fusion, which is the statistical average of a large number of information fusion errors. First, the information processing unit converts output data received from the monitoring equipment. Then, the data are fused to obtain the final information within a certain period time q. Setting the three-dimensional offset error relative to the real information as $\delta^q_1, \delta^q_2, \delta^q_3$, the total deviation (δ^q) can be calculated as follows:

$$\delta^q = \sqrt{\frac{\left(\delta^q_1\right)^2 + \left(\delta^q_2\right)^2 + \left(\delta^q_3\right)^2}{3}} \tag{8}$$

Then, the average deviation in a certain period is denoted by

$$\bar{\delta} = \frac{1}{m}\sum_{q=1}^{m} \delta^q \tag{9}$$

We can assume that the acceptable error value of information fusion in an information monitoring system is δ_{ideal}. If $\bar{\delta} < \delta_{ideal}$, the precision of information fusion $P_{23} = 1$; otherwise, $P_{23} = \delta_{ideal}/\bar{\delta}$.

d: INFORMATION FIDELITY

The fidelity of information transmission refers to the average degree of consistency between the received content and the original content under interference. By measuring the feedback data of the original data under electronic interference and network impact, we can obtain

$$P_{24} = \frac{\xi_{attact}}{\xi_{origin}} \tag{10}$$

where P_{24} represents the information fidelity of the ISNIMS, ξ_{origin} represents the original data, and ξ_{attact} represents the feedback data.

Thus, the information accuracy of the ISNIMS can be defined as follows:

$$\begin{aligned} E_{recon}^2 &= P_{recon}(I_{correcteness}) \\ &= f_{recon}^2(P_{21}, P_{22}, P_{23}, P_{24}; \omega_{21}, \omega_{22}, \omega_{23}, \omega_{24}) \end{aligned} \tag{11}$$

where $f_{recon}^2(\cdot)$ represents an aggregation function for the information accuracy, and $\omega_{21}, \omega_{22}, \omega_{23},$ and ω_{24} indicate the relative importance of the four indicators.

3) TIMELINESS

Timeliness is an indicator of the time and efficiency of information acquisition [33]. It is necessary to minimize the total time of all handling and transmission processes from the detection of target information to its acquisition [34].

The four indicators-information acquisition time, information transmission delay, data update frequency and information fusion time-are critical performance parameters in the ISNIMS, which have fixed numerical requirements. Therefore, based on the degree to which the ideal time in the monitoring process is actually met, the four indicators can be measured by the probability $P_{recon}(I_{time})$. Then, $E_{recon}^3 = P_{recon}(I_{time})$.

a: INFORMATION ACQUISITION TIME

The information acquisition time refers to the time from the start of a task to the completion of information acquisition and identification under the condition that the detection probability and the false probability specified by the information monitoring equipment are satisfied [35]. It is assumed that the ideal time of information acquisition for navigation safety is $T_{time-capture}^{ideal}$ and that the actual time of information acquisition is $T_{time-capture}$. If $T_{time-capture} < T_{time-capture}^{ideal}$, then the timeliness of information acquisition P_{31} =1; otherwise, $P_{31} = T_{time-capture}^{ideal}/T_{\ time-capture}$.

b: INFORMATION TRANSMISSION DELAY

Due to the influence of information synchronization overload and time-varying communication, there are always some delay in information transmission [36], [37]. The information transmission delay is composed of downlink delay and waiting time. The downlink delay T_{delay} can be calculated as follows:

$$T_{delay} = \frac{D}{c} + T_{ran} \tag{12}$$

where D represents the total length of the path from the detection system to the command and control center, c represents the speed of light, and T_{ran} is the value of an assignment constant related to the amount of data and the transmission speed.

The waiting time includes the buffering times of information monitoring equipment and the time required for transmission through the communication system, which can be assigned a constant value within a certain range. Thus, the information transmission delay $T_{time-delay}$ can be calculated as follows:

$$T_{time-delay} = T_{delay} + T_{wait} \tag{13}$$

It is assumed that the ideal delay of information transmission for navigation safety is $T_{time-delay}^{ideal}$. If $T_{time-delay} < T_{time-delay}^{ideal}$, then the timeliness of information transmission delay $P_{32} = 1$; otherwise, $P_{32} = T_{time-delay}^{ideal}/T_{time-delay}$.

c: DATA UPDATE FREQUENCY

The data update frequency represents the rate of exchange of all information within the monitored range per unit of time. A high data update frequency is beneficial for improving the reliability of image recognition, target recognition and signal analysis within the monitored range and to ensure effective tracking of changes in the navigational information of onboard vessels.

It is assumed that the ideal frequency of data update is $R_{data-rate}^{ideal}$, and the real frequency of data update is $R_{data-rate}$. If $R_{data-rate} > R_{data-rate}^{ideal}$, the timeliness of data update frequency $P_{33} = 1$; otherwise, $P_{33} = R_{data-rate}/R_{data-rate}^{ideal}$.

d: INFORMATION FUSION TIME

The information fusion time is closely linked to the computer processing speed, the information fusion algorithm, and the data volume. Under the premise of ensuring the integrity and accuracy of fusion processing, the shorter the fusion time is, the better the timeliness of fusion is. Assume that the ideal fusion time is $T_{time-fusion}^{ideal}$ and that the actual fusion time is $T_{time-fusion}$. If $T_{time-fusion} < T_{time-fusion}^{ideal}$, then the timeliness of information fusion $P_{34} = 1$; otherwise, $P_{34} = T_{time-fusion}^{ideal}/T_{time-fusion}$.

Therefore, we can obtain the timeliness of monitoring information as follows:

$$P_{recon}\,(I_{time}) = f_{recon}^3(P_{31}, P_{32}, P_{33}, P_{34}, \omega_{3i}) \tag{14}$$

where $f_{recon}^3(\cdot)$ represents an aggregation function for the information timeliness and $\omega_{3\mathrm{i}}$ indicates the relative importance of the four indicators ($i = 1, 2, 3, 4$).

C. EFFECTIVENESS EVALUATION BASED ON COMPREHENSIVE MEASURES

Effectiveness evaluation has undergone a development process from qualitative rough analysis to quantitative precise analysis [38]. In this process, the evaluation indicators are increasingly detailed, and the data are increasingly abundant. On the one hand, this quantitative approach can provide data guarantees for accurately implementing the effectiveness evaluation; on the other hand, it also makes selecting appropriate methods to extract the effective data from the large and complex data a major problem. Therefore, constructing a scientific and feasible data processing algorithm to correctly evaluate the system performance is the core problem in building a quantitative evaluation model. In practice, the mainstream quantitative performance evaluation models mainly adopt aggregated weight indicators under a hierarchical structure [39]. However, the singular clustering standard ignores the differences of the indicator data in the intradomain interval which increases the discrete error of the measurement data, resulting in inaccurate evaluation results. Thus, by applying intradomain range clustering to reduce the error from directly clustering the indicator data, an effectiveness evaluation model of navigational information monitoring systems based on comprehensive measures is proposed. First, the effectiveness of the system is roughly clustered. Subsequently, a precise evaluation of system effectiveness is achieved by the category adjustment coefficient.

For the objects of evaluation sample set $N = \{1, 2, \ldots, i, n-1, n\}$, we also create indicators of the evaluation sample set $M = \{1, 2, \ldots, j, m-1, m\}$. Then, under the assumption that c_{ij} represents the value of the jth indicators expressed for the ith evaluation object, we can obtain the evaluation sample matrix $\boldsymbol{C} = (c_{ij})_{n\times m}$.

We define F as the term mapping and set the evaluation rough clusters to $R = \{1, 2, \ldots, k, r-1, r\}$. Then, assuming that the expression $OPf_{jk}(c_{ij})$ is the operation for evaluation sample c_{ij} using the jth indicator in the kth rough cluster and f_{jk} as the whitening weight function for the jth indicator in the kth rough cluster [40]. If the map

$$F{:}OPf_{jk}\left(c_{ij}\right) \to \rho_{ik} \in [0, 1], \quad \rho_i = \rho_{i1}, \sigma_{i2}, \cdots, \rho_{iR}$$

is true, then map F is a type of rough cluster, and ρ_{ik} represents the weight of this rough cluster.

Applying the principle in the rough cluster on the effectiveness evaluation model of the ISNIMS, we similarly assume that the whitening weight function for the jth indicator of the evaluation sample e_{ij} in the kth rough cluster is $f_{jk}\left(c_{ij}\right)$, the adjustment coefficient for the function $f_{jk}(\cdot)$ is η_{jk}, the weight of the rough cluster is ρ_{ik}, and the vector of ρ_{ik} is $\boldsymbol{\rho_i}$.

We can obtain the rough cluster weight vector $\boldsymbol{\rho_i}$ as follows:

$$\begin{aligned}\boldsymbol{\rho_i} &= (\rho_{i1}, \rho_{i2}, \cdots, \rho_{ir}) \\ &= (\sum_{j=1}^{m} f_{j1}\left(c_{ij}\right)\cdot\eta_{j1}, \sum_{j=1}^{m} f_{j2}\left(c_{ij}\right)\cdot\eta_{j2}, \cdots, \sum_{j=1}^{m} f_{jr}\left(c_{ij}\right)\cdot\eta_{jr})\end{aligned} \tag{15}$$

Then, we can obtain the unitization evaluation coefficient δ_{ik} as follows:

$$\delta_{ik} = \rho_{ik} \Big/ \sum_{k=1}^{r} \rho_{ik} \tag{16}$$

By setting the unitization evaluation coefficient vector for object i to $\boldsymbol{\delta}_i{=}(\delta_{i1}, \delta_{i2}, \cdots, \delta_{ir})$, we can obtain the unitization evaluation coefficient matrix as $\boldsymbol{\omega} = (\delta_{ik})_{n\times r}$.

Additionally, the adjustment coefficient $\boldsymbol{\eta}_k$ of the evaluation rough clusters is

$$\begin{cases} \boldsymbol{\eta}_1 = (r, r-1, r-2, \cdots, 1) \\ \boldsymbol{\eta}_2 = (r-1, r, r-1, r-2, \cdots, 2) \\ \boldsymbol{\eta}_1 = (r-2, r-1, r, r-1, r-2\cdots, 3) \\ \quad\vdots \\ \boldsymbol{\eta}_k = (r-1, r-k+2, \cdots, r-1, r, r-1, \cdots, k) \\ \quad\vdots \\ \boldsymbol{\eta}_{r-1} = (2, 3, \cdots + 1, r, r-1) \\ \boldsymbol{\eta}_r = (1, 2, 3, \cdots, r-1, r) \end{cases} \tag{17}$$

We set $\max\limits_{1\le k\le r}\{\delta_{ik}\} = \delta_{ik^*}$. Judged by the value of $\max\limits_{1\le k\le r}\{\delta_{ik}\}$, object i was classified into rough cluster k^*, so the adjustment coefficient $\boldsymbol{\eta}_{ik} = \boldsymbol{\eta}_{k^*}$. Then, the absolute evaluation results $\boldsymbol{e}_{i\_absolute}$ and comprehensive effectiveness evaluation results $\boldsymbol{e}_i$ can be calculated as follows:

$$\boldsymbol{e}_i = \frac{\boldsymbol{e}_{i\_absolute}}{\boldsymbol{e}_{ideal}} = \frac{\boldsymbol{\eta}_{ik}\cdot\boldsymbol{\delta}_i^T}{\boldsymbol{e}_{ideal}} = \frac{\boldsymbol{\eta}_{k^*}\cdot\boldsymbol{\delta}_i^T}{\boldsymbol{e}_{ideal}} \tag{18}$$

D. EFFECTIVENESS ANALYSIS BASED ON ORTHOGONAL EXPLORATION

The analysis of the orthogonal exploration test results included two parts, the factor effect estimation and the analysis of significance. For the former, we used a small amount of testing data to extrapolate the technical performance of the system composition with different factors and different levels. The latter was used mainly to perform the significance test of the factors, to determine which factors that had an effect on performance were significant, to determine the best combination of factors at various levels, and to estimate the testing error.

1) FACTOR EFFECT ESTIMATION

For the factors of the test sample set $P = \{1, 2, 3, \ldots, i, \ldots, k-1, k\}$, we created an indicator of the component capability level set $Q = \{1, 2, 3, \ldots, j, \ldots, q-1, q\}$, under the assumption that e_{ijm} represents the mth test result of the jth indicator level expressed for the ith factor. We obtained the sum of the test results T_{ij} as follows:

$$T_{ij} = \sum_{m=1}^{M} e_{ijm} \tag{19}$$

Then, we calculated the average value of the test results of different factors at different levels $\bar{T}_{ij}$ and the average of total test results $\hat{U}$ as follows:

$$\bar{T}_{ij} = \frac{T_{ij}}{M} \tag{20}$$

$$\hat{U} = \frac{1}{N}\sum_{m=1}^{N} e_m \tag{21}$$

where e_m represents the mth test results and N represents all test times. Then, we obtained the range R_i and effect estimation $\bar{\bar{T}}_{ij}$ of different factors at different levels as follows:

$$R_i = \max_{1\le j\le k}\left(\bar{T}_{ij}\right) - \min_{1\le j\le k}\left(\bar{T}_{ij}\right) \tag{22}$$

$$\bar{\bar{T}}_{ij} = \bar{T}_{ij} - \hat{U} \tag{23}$$

Through these three steps, we carried out an intuitive analysis of the test results. From the table showing the analysis of the test results, we can directly find out the better combination of test factors. By comparing the average test results $\bar{T}_{ij}$ under each level for each factor, we can theoretically obtain the best combination scheme of average test results for each factor. From the size of range R_i, we can judge the influence of each factor on the test results. The larger the range, the greater the effect of the factor on the test results. From the effect estimation $\bar{\bar{T}}_{ij}$, we can estimate the performance of any combination of factors and levels.

2) SIGNIFICANCE ANALYSIS

Step1: Calculate the sum of the squared deviations and the degrees of freedom for each factor. The sum of the squared deviations for the ith factor S_i^2 and its degrees of freedom f_i are as follows:

$$S_i^2 = \sum_{j=1}^{q} \bar{\bar{T}}_{ij}^2 r, f_i = q - 1 \tag{24}$$

where r represents the number of repeated tests at each level.

Step2: Calculate the total sum of squares S^2 as follows:

$$S^2 = \sum_{m=1}^{N} (e_m - \hat{U})^2 \tag{25}$$

Step3: Calculate the error sum of squares S_e^2. It consists of the sum of squares of blank columns, and its degree of freedom f_e is also the sum of the degrees of freedom for the blank columns.

$$S_e^2 = \sum_{d=1}^{D} S_{ed}^2 \tag{26}$$

$$f_e = \sum_{d=1}^{D} f_{ed} \tag{27}$$

where S_{ed}^2, f_{ed} respectively represent the sum of the squares of deviations and the degree of freedom for the dth blank factor $(1 \le d \le D)$.

Step4: Variance analysis. Calculate the F-distribution ratio value, and then determine the rejection region W at the given significance level α as follows:

$$F_i = \frac{S_i^2/f_i}{S_e^2/f_e} \tag{28}$$

$$W = \{F_i > F_\alpha(f_i, f_e)\} \tag{29}$$

where $F_\alpha(f_i, f_e)$ express the upper critical values of the F-distribution at the α significance level.

According to the analysis of variance results, we can determine the significance factor and influence intensity, and then determine the optimal level match according to the significance factor level and effect.

IV. APPLICATION OF METHODOLOGY

A. CASE SELECTION AND DATA ACQUISITION

Based on the intelligent ship navigational information monitoring platform in the test ship named Yukun, we carried out an orthogonal exploratory test of the navigational information monitoring system, to verify whether the methodology could effectively identify the significance and contribution of each subsystem proposed in section II.A. This test was based on the intelligent transformation of the actual ship. The main data types we collected were based on the navigation interaction information needed by Yukun to complete the navigation transformation of intelligent ships, and then we tested and verified it through the changes of interaction frequency, volume and complexity. We took the data as the input and the indicator results under the test as the output. Then we monitored the effectiveness change of the system and the performance difference under different indicator data. To improve the data consistency, the same set of data measurement standards was used to collect data from all tests.

Based on the orthogonal test design in section III.A and its corresponding interaction list, we set the parameter value of each subsystem as level 3 standard and arranged the test by the orthogonal table L27(3^{13}), which means 13 factors, 3 levels and 27 tests. The test data and corresponding effectiveness evaluating value are shown in appendix. A [41].

B. RESULTS AND ANALYSIS

Based on the model algorithm and corresponding orthogonal test interaction list, we conduct an exploratory analysis of effectiveness evaluation value for the ISNIMS, the statistics and calculation results are shown in Table 3.

1) FACTOR EFFECT ANALYSIS

In Table 3, the test results showed that the most effective factor was $e_{27} = 0.98$, and the factor level combination was A(level 3), B(level 3), C(level 3), D(level 2), E(level 3). From the theoretical average value $\bar{T}_{ij}$, the best combination scheme of each factor was A(level 3), B(level 3), C(level 3), D(level 3), E(level 3). The range data R_i was used to determine the importance of each subsystem. It can be determined that the maximum range of ICS was 0.1311, indicating that

TABLE 3. Orthogonal exploratory analysis values of system effectiveness under interaction in the first round of tests.

Test order	C	A	(C×A)₁	(C×A)₂	E	(C×E)₁	(C×E)₂	D	(C×D)₁	(C×D)₂	Blank	B	Blank	e_i
1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.74
2	1	1	1	1	2	2	2	2	2	2	2	2	2	0.82
3	1	1	1	1	3	3	3	3	3	3	3	3	3	0.88
4	1	2	2	2	1	1	1	2	2	2	3	3	3	0.87
5	1	2	2	2	2	2	2	3	3	3	1	1	1	0.79
6	1	2	2	2	3	3	3	1	1	1	2	2	2	0.8
7	1	3	3	3	1	1	1	3	3	3	2	2	2	0.85
8	1	3	3	3	2	2	2	1	1	1	3	3	3	0.77
9	1	3	3	3	3	3	3	2	2	2	1	1	1	0.88
10	2	1	2	3	1	2	3	1	2	3	1	2	3	0.73
11	2	1	2	3	2	3	1	2	3	1	2	3	1	0.80
12	2	1	2	3	3	1	2	3	1	2	3	1	2	0.87
13	2	2	3	1	1	2	3	2	3	1	3	1	2	0.85
14	2	2	3	1	2	3	1	3	1	2	1	2	3	0.9
15	2	2	3	1	3	1	2	1	2	3	2	3	1	0.85
16	2	3	1	2	1	2	3	3	1	2	2	3	1	0.94
17	2	3	1	2	2	3	1	1	2	3	3	1	2	0.82
18	2	3	1	2	3	1	2	2	3	1	1	2	3	0.85
19	3	1	3	2	1	3	2	1	3	2	1	3	2	0.97
20	3	1	3	2	2	1	3	2	1	3	2	1	3	0.96
21	3	1	3	2	3	2	1	3	2	1	3	2	1	0.92
22	3	2	1	3	1	3	2	2	1	3	3	2	1	0.97
23	3	2	1	3	2	1	3	3	2	1	1	3	2	0.94
24	3	2	1	3	3	2	1	1	3	2	2	1	3	0.93
25	3	3	2	1	1	3	2	3	2	1	2	1	3	0.95
26	3	3	2	1	2	1	3	1	3	2	3	2	1	0.96
27	3	3	2	1	3	2	1	2	1	3	1	3	2	0.98
T_1	7.4000	7.6900	7.8900	7.9300	7.8700	7.8900	7.8100	7.5700	7.9300	7.6200	7.7800	7.7900	7.8500	
T_2	7.6100	7.9000	7.7500	7.9200	7.7600	7.7300	7.8400	7.9800	7.7800	8.1400	7.9000	7.8000	7.9000	
T_3	8.5800	8.0000	7.9500	7.7400	7.9600	7.9700	7.9400	8.0400	7.8800	7.8300	7.9100	8.0000	7.8400	
$\overline{T}_1$	0.8222	0.8544	0.8767	0.8811	0.8744	0.8767	0.8678	0.8411	0.8811	0.8467	0.8644	0.8656	0.8722	
$\overline{T}_2$	0.8456	0.8778	0.8611	0.8800	0.8622	0.8589	0.8711	0.8867	0.8644	0.9044	0.8778	0.8667	0.8778	
$\overline{T}_3$	0.9533	0.8889	0.8833	0.8600	0.8844	0.8856	0.8822	0.8933	0.8756	0.8700	0.8789	0.8889	0.8711	
R_i	0.1311	0.0344	0.0222	0.0211	0.0222	0.0267	0.0144	0.0522	0.0167	0.0578	0.0144	0.0233	0.0067	
$\overline{\overline{T}}_1$	0.0515	0.0193	0.0030	0.0074	0.0007	0.0030	0.0059	0.0326	0.0074	0.0270	0.0093	0.0081	0.0015	
$\overline{\overline{T}}_2$	0.0281	0.0041	0.0126	0.0063	0.0115	0.0148	0.0026	0.0130	0.0093	0.0307	0.0041	0.0070	0.0041	
$\overline{\overline{T}}_3$	0.0796	0.0152	0.0096	0.0137	0.0107	0.0119	0.0085	0.0196	0.0019	0.0037	0.0052	0.0152	0.0026	
S_i^2	0.0881	0.0056	0.0023	0.0025	0.0022	0.0033	0.0010	0.0145	0.0013	0.0152	0.0012	0.0031	0.0002	
S^2	0.1406													
S_e^2	0.0014													
f_i	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	
f_e	4.0000													
F-dis rate	126.4574	7.9894	3.3617	3.6489	3.2021	4.7660	1.4787	20.8830	1.8617	21.8404	1.6702	4.4787	0.3298	

T_1, T_2, T_3 refer to the sum of test results in level 1, 2, 3. $\overline{T}_1, \overline{T}_2, \overline{T}_3$ refer to the average of T_1, T_2, T_3. R_i refers to the range in each T_{ij}. $\overline{\overline{T}}_1, \overline{\overline{T}}_2, \overline{\overline{T}}_3$ refer to the effect estimation of different factors at different levels. S_i^2 refers to the sum of the squared deviations of the ith factor. S^2 refers to the total sum of squares. S_e^2 refers to the sum of squared errors. f denotes the degree of freedom. f_e denotes the degree of freedom about S_e.

ICS had the greatest impact on the system effectiveness. The maximum range of IDS was 0.222, and the maximum range of IFS was 0.233, indicating that these two subsystems had a similar impact on the system effectiveness. However, due to the interaction between IDS and ICS, it was impossible to determine the actual degree of impact. The influence trend chart of each subsystem on the system effectiveness was constructed as shown in Figure 7.

In Figure 7, it can be seen that the stronger the operating ability of ICS, the greater the system operation effectiveness, and the more obvious the multiplier effect. IPS, IFS and IDMS also had a positive relationship to the system monitoring effectiveness, but the multiplier effect was slightly lower.

2) VARIANCE ANALYSIS

In this case, the interaction occupies two columns, so the sum of squared variation of the interaction is equal to the sum of the squared variation of the corresponding two columns, as follows:

$$\begin{cases} S_{C\times A}^2 = S_3^2 + S_4^2 = 0.0023 + 0.0025 = 0.0048 \\ S_{C\times D}^2 = S_6^2 + S_7^2 = 0.0033 + 0.0010 = 0.0043 \\ S_{C\times E}^2 = S_9^2 + S_{10}^2 = 0.0013 + 0.0125 = 0.0165 \end{cases}$$

At the same time, it can be seen from Table 3 that the 11th and 13th columns are blank as error columns, so the sum of squared errors and the degree of freedom for the error

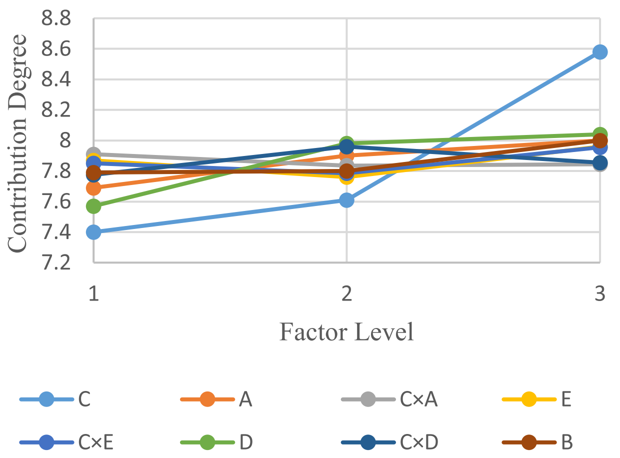

FIGURE 7. Trends of factor contributions to system effectiveness.

TABLE 4. The analysis of variance.

Variation	S_i^2	f_i	S_i^2/f_i	F_i	Significance
A	0.0056	2	0.0028	7.989362	*
B	0.0031	2	0.00155	4.478723	
C	0.0881	2	0.04405	126.4574	***
D	0.0145	2	0.00725	20.88298	**
E	0.0022	2	0.0011	3.202128	
A×C	0.0048	4	0.0012	7.010638	*
C×D	0.0043	4	0.001075	23.70213	**
C×E	0.0165	4	0.004125	6.244681	

S_i^2 refers to the sum of the squared deviations of the ith factor. f_i refers to the degree of freedom. F_i refers to F-distribution ratio value of the ith factor. The number of * refers to the degree of significance.

columns can be calculated as follows:

$$\begin{cases} S_e^2 = S_{11}^2 + S_{13}^2 = 0.0014 \\ f_e = 2 + 2 = 4 \end{cases}$$

So, we can obtain the analysis of variance as follows in Table 4:

When $\alpha = 0.05$ was selected, it can be found from the critical value table of F-distribution that $F_{1-0.05}(2, 4) = 6.94$ and $F_{1-0.05}(4, 4) = 6.00$. Consequently, we determined that factor C had a highly significant effect on system effectiveness, while factor D and the interaction, C×D, were secondarily significant. According to the F values of the subsystems, the contribution distribution can be obtained as follows in Figure 8:

In order to verify the robustness of the orthogonal exploration analysis methodology, the requirements for the system to complete the specified task were adjusted, and the same test methodology was used for analysis. The test data and corresponding effectiveness evaluating value were shown in appendix. B [42]. The analysis calculation results were shown in Table 5. Compared with the first round

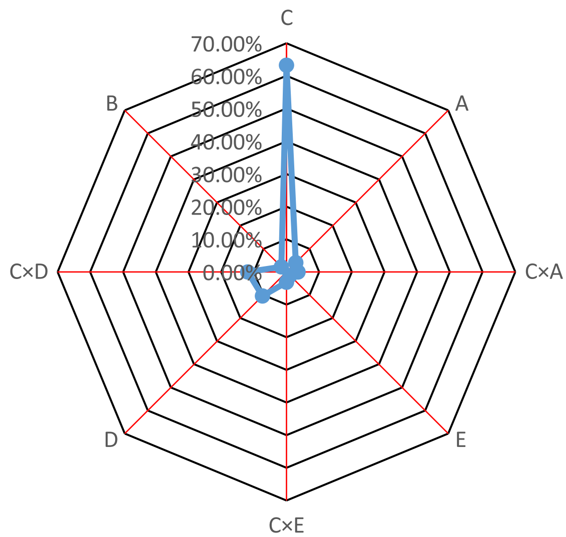

FIGURE 8. System effectiveness contribution degree distribution.

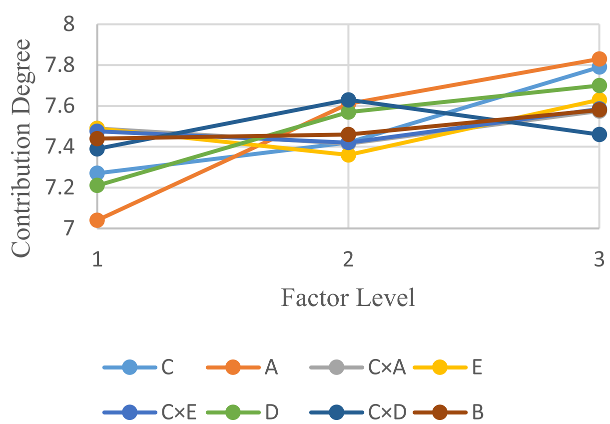

FIGURE 9. Trends of factor contributions to system effectiveness in the second round of tests.

of tests, the requirements for this task were improved, and the corresponding value range of effectiveness was changed accordingly. The influence trend and contribution distribution of each subsystem on the system effectiveness was shown in Figure 9 and Figure 10.

C. DISCUSSION

Through the analysis of the contribution degree trends (Figure 7 and Figure 9), it was found that the relationship between exploratory analysis factors and effectiveness showed a positive overall trend, indicating that the measured values of this methodology were consistent with the actual state. However, based on Figure 7 and Figure 9, we found a special phenomenon in which the influence of IDS on the system effectiveness showed an anti-correlation trend at the second level, indicating that when the IDS was at the second level, the contribution of the IDS to the system effectiveness showed a downward trend. As shown in Figure 11, the reference standards for the capability setting of

TABLE 5. Orthogonal exploratory analysis values of system effectiveness under interaction in the second round of tests.

Test order	C	A	$(C\times A)_1$	$(C\times A)_2$	E	$(C\times E)_1$	$(C\times E)_2$	D	$(C\times D)_1$	$(C\times D)_2$	Blank	B	Blank	e_i
1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.68
2	1	1	1	1	2	2	2	2	2	2	2	2	2	0.77
3	1	1	1	1	3	3	3	3	3	3	3	3	3	0.82
4	1	2	2	2	1	1	1	2	2	2	3	3	3	0.85
5	1	2	2	2	2	2	2	3	3	3	1	1	1	0.77
6	1	2	2	2	3	3	3	1	1	1	2	2	2	0.79
7	1	3	3	3	1	1	1	3	3	3	2	2	2	0.88
8	1	3	3	3	2	2	2	1	1	1	3	3	3	0.79
9	1	3	3	3	3	3	3	2	2	2	1	1	1	0.92
10	2	1	2	3	1	2	3	1	2	3	1	2	3	0.7
11	2	1	2	3	2	3	1	2	3	1	2	3	1	0.76
12	2	1	2	3	3	1	2	3	1	2	3	1	2	0.83
13	2	2	3	1	1	2	3	2	3	1	3	1	2	0.85
14	2	2	3	1	2	3	1	3	1	2	1	2	3	0.91
15	2	2	3	1	3	1	2	1	2	3	2	3	1	0.85
16	2	3	1	2	1	2	3	3	1	2	2	3	1	0.92
17	2	3	1	2	2	3	1	1	2	3	3	1	2	0.80
18	2	3	1	2	3	1	2	2	3	1	1	2	3	0.80
19	3	1	3	2	1	3	2	1	3	2	1	3	2	0.83
20	3	1	3	2	2	1	3	2	1	3	2	1	3	0.82
21	3	1	3	2	3	2	1	3	2	1	3	2	1	0.83
22	3	2	1	3	1	3	2	2	1	3	3	2	1	0.88
23	3	2	1	3	2	1	3	3	2	1	1	3	2	0.84
24	3	2	1	3	3	2	1	1	3	2	2	1	3	0.87
25	3	3	2	1	1	3	2	3	2	1	2	1	3	0.90
26	3	3	2	1	2	1	3	1	3	2	3	2	1	0.90
27	3	3	2	1	3	2	1	2	1	3	1	3	2	0.92
T_1	7.2700	7.0400	7.3800	7.6000	7.4900	7.4500	7.5000	7.2100	7.5400	7.2400	7.3700	7.4400	7.5100	
T_2	7.4200	7.6100	7.4200	7.4100	7.3600	7.4200	7.4200	7.5700	7.4600	7.8000	7.5600	7.4600	7.5100	
T_3	7.7900	7.8300	7.6800	7.4700	7.6300	7.6100	7.5600	7.7000	7.4800	7.4400	7.5500	7.5800	7.4600	
$\overline{T}_1$	0.8078	0.7822	0.8200	0.8444	0.8322	0.8278	0.8333	0.8011	0.8378	0.8044	0.8189	0.8267	0.8344	
$\overline{T}_2$	0.8244	0.8456	0.8244	0.8233	0.8178	0.8244	0.8244	0.8411	0.8289	0.8667	0.8400	0.8289	0.8344	
$\overline{T}_3$	0.8656	0.8700	0.8533	0.8300	0.8478	0.8456	0.8400	0.8556	0.8311	0.8267	0.8389	0.8422	0.8289	
R_i	0.0578	0.0878	0.0333	0.0211	0.0300	0.0211	0.0156	0.0544	0.0089	0.0622	0.0211	0.0156	0.0056	
$\overline{\overline{T}}_1$	0.0248	0.0504	0.0126	0.0119	0.0004	0.0048	0.0007	0.0315	0.0052	0.0281	0.0137	0.0059	0.0019	
$\overline{\overline{T}}_2$	0.0081	0.0130	0.0081	0.0093	0.0148	0.0081	0.0081	0.0085	0.0037	0.0341	0.0074	0.0037	0.0019	
$\overline{\overline{T}}_3$	0.0330	0.0374	0.0207	0.0026	0.0152	0.0130	0.0074	0.0230	0.0015	0.0059	0.0063	0.0096	0.0037	
S_i^2	0.0881	0.0056	0.0023	0.0025	0.0022	0.0033	0.0010	0.0145	0.0013	0.0152	0.0012	0.0031	0.0002	
S^2	0.1049													
S_e^2	0.0027													
f_i	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	
f_e	4.0000													
F-dis rate	11.6793	27.1033	4.3261	1.5380	2.9728	1.7011	0.8043	10.5054	0.2826	13.1304	1.8641	0.9348	0.1359	

T_1, T_2, T_3 refer to the sum of test results in level 1, 2, 3. $\overline{T}_1, \overline{T}_2, \overline{T}_3$ refer to the average of T_1, T_2, T_3. R_i refers to the range in each T_{ij}. $\overline{\overline{T}}_1, \overline{\overline{T}}_2, \overline{\overline{T}}_3$ refer to the effect estimation of different factors at different levels. S_i^2 refers to the sum of the squared deviations of the ith factor. S^2 refers to the total sum of squares. S_e^2 refers to the sum of squared errors. f denotes the degree of freedom. f_e denotes the degree of freedom about S_e.

each subsystem corresponded to the classification standards of the interconnection, remote control, and autonomous navigation of intelligent ships. In the remote controlling stage, the navigation instructions mainly depended on the release of the remote center, not on the IPS, and its effectiveness contribution decreased at Level 2 [43]. At the same time, the rapid increase of the data at level 3 shown in Figure 7 and Figure 9 indicated that the contribution of IPS to the system effectiveness increased significantly during the autonomous navigation phase, which is in line with the increased dependence of intelligent ships on the IPS in the autonomous navigation phase. It also further verified the scientific nature of this methodology.

Comparing Figure 7 and Figure 9, it could be found that regardless of the degree of completion specified, the contribution degree trend of the subsystems to the system effectiveness was consistent. Comparing Figure 8 and Figure 10, as shown in Figure 12, it could be found that for systems equipped with the same monitoring hardware, the change in the contribution degree of the subsystems will lead to changes

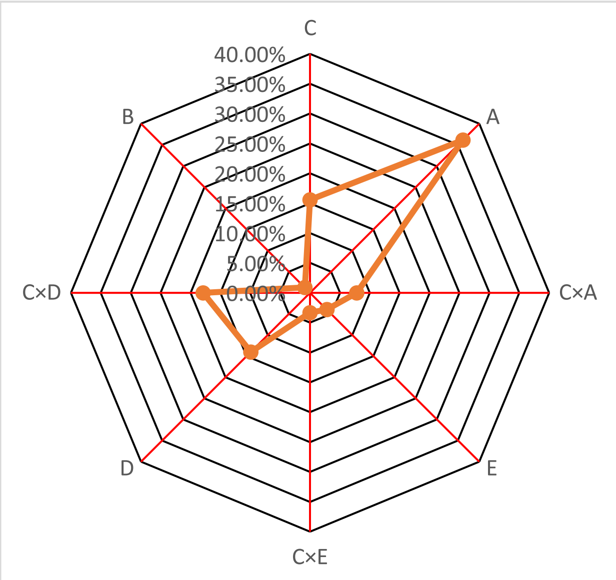

FIGURE 10. Degree and distribution of system effectiveness contributions in the second round of tests.

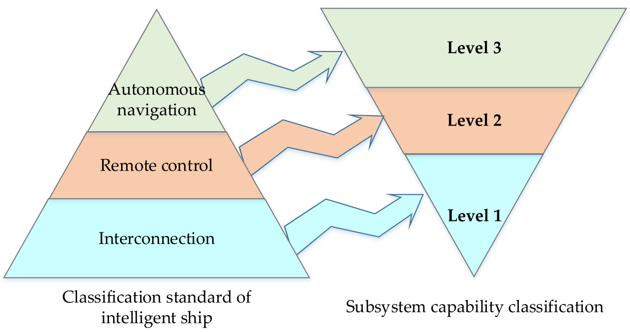

FIGURE 11. Exploratory analysis factor level setting reference.

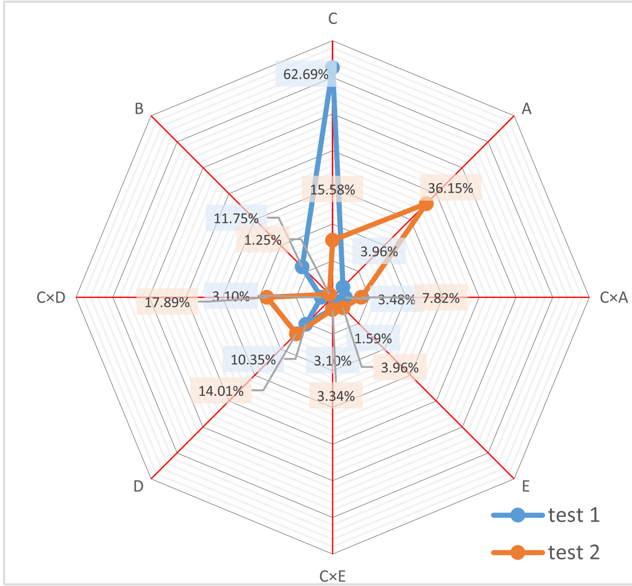

FIGURE 12. Comparison of the results in the first and second round of tests.

in the system effectiveness, and vice versa. If the system effectiveness changes while the system structure, external environment, and conditions remain unchanged, it must be because the contribution degree of the subsystems to the system has changed. This conclusion also implies that the exploratory analysis methodology based on orthogonal test is reasonable, feasible and effective. The weight of the contribution in Figure 8 showed that in the first round of tests, the contribution degree of the ICS to the system effectiveness was 63.24%, indicating that the achievement of the first round of measurement goals depended more on the performance of the ICS. The high-capacity requirements of the communication system were consistent with the interconnection and interoperability features of the first-level intelligent ship. The contribution degree in Figure 10 showed that in the second round of tests, IPS, IDMS and ICS had greater weight, indicating that the measurement target in this round was more dependent on intelligent perception, decision-making and communication. This is also consistent with the high-level requirements of the autonomous navigation characteristics of third-level intelligent ships for sensing and autonomous decision-making technology. The two weight changes were consistent with the actual differences in effectiveness goals, further verifying that the exploratory analysis methodology has excellent discriminability.

Compared with the traditional methodology for evaluating system effectiveness, our approach provides a reference for comprehensive understanding of the degree of contribution of various uncertainty factors to system effectiveness. However, the methodology can only be used to analyze the system in a static state, while in reality, monitoring a ship's navigational information is a long-term dynamic process. Our methodology can only measure the effectiveness of the system from a macro perspective, and the evaluation under conditions of dynamic changes requires further study. The next step is to conduct dynamic simulation research from the perspective of multi- agent modeling.

V. CONCLUSION

Sustaining the safety of an intelligent ship through navigational stability is highly reliant on the effectiveness of the ship's navigational information monitoring system. To comprehensively evaluate the interaction and correlation strength between navigational information monitoring system and its subsystems, this study developed an exploratory analysis methodology based on orthogonal test. Beginning with the analysis of information behavior characteristics, the interaction relationship and ability level division standards of the ISNIMS were established by reference to the intelligent ship technology development path: interconnection, remote control, and autonomous navigation. The orthogonal test method was used to reduce the number of tests required and to improve the application scope and measurement efficiency of the methodology under the testing premises. By measuring the test results under different combinations of factors, the internal relationship between subsystems and system effectiveness was determined. The test case results showed that the exploratory analysis methodology based on information behavior characteristics accurately measured the degree of contribution of the subsystems to the system effectiveness and proved that the orthogonal test method effectively improved the robustness of the methodology.

Our study presents a more comprehensive and effective uncertainty analysis methodology for complex systems. Instead of a simple sensitivity analysis of small-scale changes under an optimal solution, the degree of contribution of uncertainty factors and system effectiveness is measured based on the creation of a comprehensive combination of different factors. This ensures good applicability for evaluating the effectiveness of navigational systems on multi-level intelligent ships. The methodology correlates the capacity division of component units with the intelligent ship classification standards and only collects data related to navigational information. It does not analyze the characteristics of the ship itself, and thus, the evaluation methodology has good universality. The exploratory analysis methodology utilizes the method of orthogonal test to improve the efficiency and robustness of the contribution degree analysis by reducing the number of tests and optimizing the test design.

APPENDIX A

Research data in the first round of tests: https://doi.org/10.17632/SVZ8HMCCSV.3.

APPENDIX B

Research data in the second round of tests: https://doi.org/10.17632/3WCJKFR856.3.

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